Performance Evaluation of Cognitive Radio Spectrum Sensing Techniques through a Rayleigh Fading Channel

by

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Declaration

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Dedication

To my family and friends. Special mention goes to my brother Jubilant Shumba, my friends Artwell Bhebhe and Trynos Chivengese for the moral support.

Abstract

In recent years, there has been a steep rise in the demand for bandwidth due to a sharp increase in the number of devices connected to the wireless network. Coupled with the expected commercialization of 5G services and massive adoption of IoT, the upsurge in the number of devices connected to the wireless network will continue to grow exponentially into billions of devices. To accommodate the associated demand for wireless spectrum as we step into this new era of wireless connectivity, traditional methods of spectrum utilization based on fixed and static allocation are no longer adequate. New innovative forms that support dynamic assignment of spectrum space on as-per-need basis are now paramount. Cognitive radio has emerged as one of the most promising techniques that allow flexible usage of the scarce spectrum resource. Cognitive radio allows unlicensed users to opportunistically access spectrum bands assigned to primary users when these spectrum bands are idle. As such, cognitive radio reduces the gap between spectrum scarcity and spectrum underutilization. The most critical function of cognitive radio is spectrum sensing, which establishes the occupation status of a spectrum band, paving the way for a cognitive radio to initiate transmission if the band is idle. The most common and widely used methods for spectrum sensing are energy detection, matched filter detection, cyclostationary feature detection and cooperative based spectrum sensing.

This dissertation investigates the performance of these spectrum-sensing techniques through a Rayleigh fading channel. In a wireless environment, a Rayleigh fading channel models the propagation of a wireless signal where there is no dominant line of sight between the transmitter and receiver. Understanding the performance of spectrum sensing techniques in a real world simulation environment is important for both industry and academia, as this allows for the optimal design of cognitive radio systems capable of efficiently executing their function. MATLAB software provides an experimental platform for the fusion of various Rayleigh fading channel parameters that mimic real world wireless channel characteristics. In this project, a MATLAB environment test bed is used to simulate the performance for each spectrum sensing technique across a range of signal-to-noise values, through a Rayleigh fading channel with a given set of parameters for channel delay, channel gain and Doppler shift. Simulation results are presented as plots for probability of detection versus signal-to-noise ratio, receiver operating characteristics (ROC) curves and complementary ROC curves. A detailed performance analysis for each spectrum sensing technique then follows, with comparisons done to determine the technique that offers the best relative performance.

Acknowledgements

I would like to express my utmost gratitude to my supervisors Dr Simon Winberg and Dr Ettiene Feukeu for the guidance and support they provided during the course of this work. Without their support, this thesis would not have been a success.

NOMENCLATURE

5G	Fifth Generation
ASK	Amplitude Shift Keying
BS	Base Station
CFD	Cyclostationary Feature Detection
CR	Cognitive Radio
DSA	Dynamic Spectrum Access
ED	Energy Detection
FC	Fusion Centre
FFT	Fast Fourier Transform
FSK	Frequency Shift Keying
GLRT	Generalised Likelihood Ratio Test
GSM	Global System for Mobile Communications
IoT	Internet of Things
ISM	Industrial, Scientific and Medical
MFD	Matched Filter Detection
PDA	Personal Digital Assistant
PU	Primary User
PSK	Phase Shift Keying
RF	Radio Frequency
ROC	Receiver Operating Characteristics
SCF	Spectral Correlation Function
SDR	Software Defined Radio
SNR	Signal To Noise Ratio
SU	Secondary User
WLAN	Wireless Local Area Network
WRAN	Wireless Regional Area Networks
WSN	Wireless Sensor Network
USRP	Universal Software Radio Periphera

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CHAPTER ONE

1 INTRODUCTION

The purpose of this dissertation is to design and implement a test-bed for the evaluation of the performance of various spectrum-sensing techniques in a cognitive radio. The spectrum sensing techniques considered in this work are energy detection, cyclostationary feature detection, matched filter detection and energy detection based co-operative technique, and simulation is through a Rayleigh fading channel. This is aimed at assisting designers choose a spectrum sensing technique implementation, based on results obtained from a test-bed that mimics the practical environmental conditions in which a cognitive radio operates. The variable environmental conditions under which the performance of the spectrum sensing techniques are investigated include signal to noise ratio, doppler shift, channel delays and gains and the results are presented in the form of receiver operating characteristics and complementary receiver operating characteristics curves.

1.1 Overview

It is expected that the commercialization of 5G in 2020 will be massive; it will trigger an even greater upsurge in the number of devices connected to the wireless network. According to a forecast by Ericsson, an estimated 70% of wide-area IoT devices will use cellular technology in 2022 [1] . In addition, about 28 billion connected devices are forecasted by 2021 [2] (see trend in Figure 1-1). IDTechX, a market research group which conducts detailed examination on emerging technologies, reinforces these findings by reporting that the wireless sensor network market will grow to $1.8 billion Compound Annual Growth Rate by 2024[3].

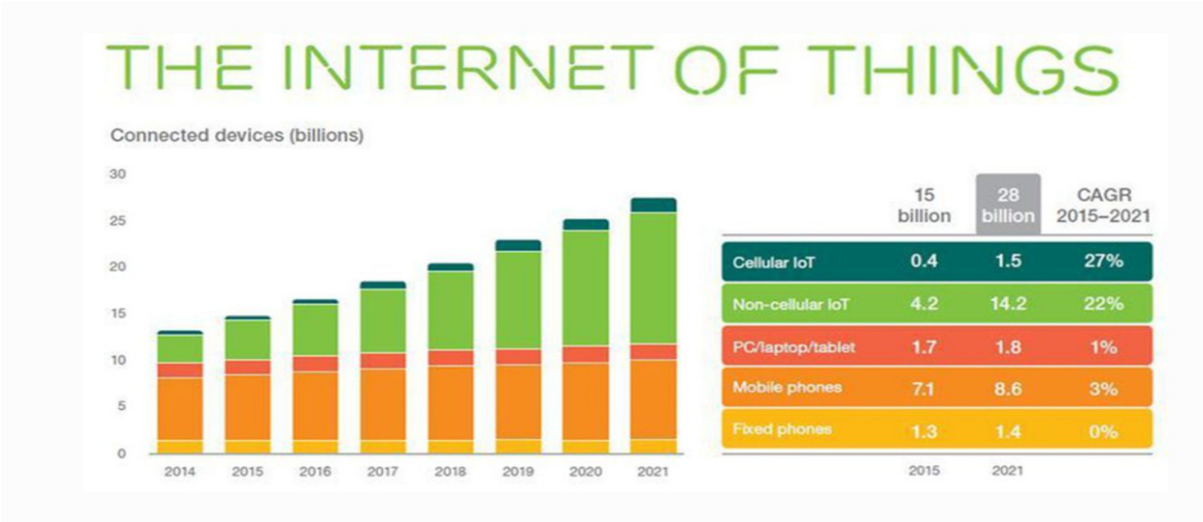

Figure 1-1: IoT growth rate forecast according to Ericson [2]

These developments naturally stimulate a higher demand for the frequency spectrum resource. Subsequently, substantial research effort is now focusing on finding solutions that will cater for the increased demand for network connectivity by the IoT devices and wireless sensor networks. Electromagnetic spectrum is an essential and precious resource in the realisation of wireless radio communication. Worldwide, spectrum is managed strictly by regulation, to promote orderly and efficient use in the delivery of voice, data and multimedia services. Traditionally, countries and their respective regulatory bodies manage the spectrum resource relating to public and private use, interference minimization as well as addressing health and safety issues. A widely used method for spectrum allocation is the licensing technique, where central governments and regulatory bodies divide the spectrum and allocate fixed portions to licensees at a cost [4]. As shown through various spectrum occupancy campaigns, the major problem arising from this policy is the underwhelming spectrum utilization [5][6]. Clearly, the current fixed allocation policy where central governments allocate spectrum to licensed operators, for use in a given geographic location at a cost, cannot sustain and support the demands that come with the growth in the number of wireless devices that need network connectivity and the associated bandwidth.

Since at any given time, there exists spectrum holes in both the time and spatial domains, these white spaces can be exploited opportunistically by other users leading to the concept of dynamic spectrum access [7]. Radio devices are equipped with the capability to be intelligently aware of the environment in which they operate in order to exploit spectrum gaps without inconveniencing licensed spectrum users. This new paradigm is known as Cognitive Radio, and is seen as a promising solution to the problem of spectrum scarcity through efficient spectrum resource utilization, as demonstrated in the IEEE802.22 standard for Wireless Regional Area Networks (WRANs)[8]. These networks exploit white spaces in the VHF and UHF bands of the television band channels to provide both fixed and mobile high throughput, long-range communications.

By definition, a Cognitive Radio (CR) is a radio with the capability to observe and learn from its operating environment and adapt its transmission and reception parameters in such a manner that optimises the network performance [9]. CR allows unlicensed users (secondary users) to access spectrum opportunistically when the licensed users (primary users) are not using it as shown in Figure 1-2. This intelligent and flexible use of available spectrum is known as dynamic spectrum access (DSA).

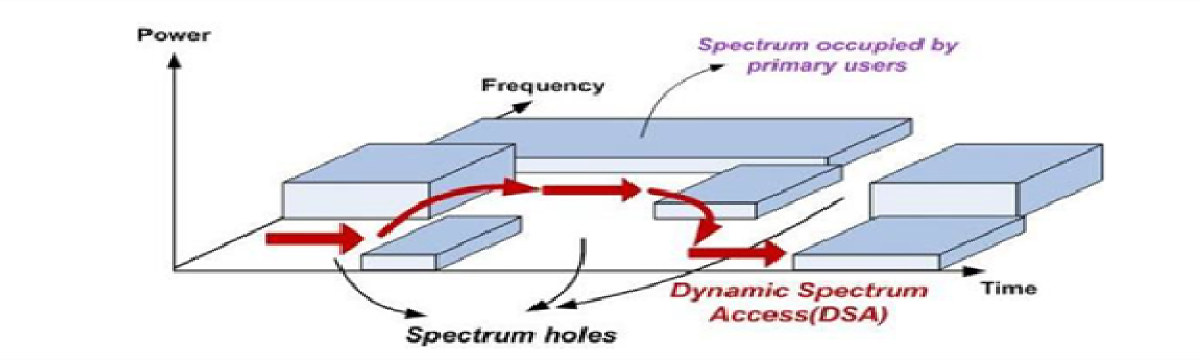

Figure 1 2: Three Dimensional view on how Power, Frequency and Time domains are used in Dynamic Spectrum Access.

The goal of dynamic spectrum access is to identify and exploit unused spectrum opportunities in the bands assigned to the primary users. A key aspect in the implementation of CR is the stringent requirement to avoid interference and degradation to the transmission and reception of the primary user. Minimum interference to the primary user can only be guaranteed by using an effective spectrum sensing technique.

The overall aim of this work is to analyse and evaluate the performance of fundamental spectrum sensing techniques namely energy detection, cyclostationary feature detection and matched filter detection, under Rayleigh fading channel conditions.

The dissertation also investigates the performance of energy detection based co-operative spectrum sensing and provides a basis for performance comparison with the fundamental spectrum sensing techniques mentioned earlier. This introductory chapter presents background information and defines the scope and objectives of this study.

1.2 Background and Motivation

Numerous studies undertaken in different geographical areas show the existence of spectrum holes in the spatial, frequency and time domains. With the forecasted growth of wireless sensor networks [3] , and with the current scenario where most WSN utilize the congested unlicensed ISM band, dynamic spectrum access offers a realistic avenue to enhance the performance of future WSN. Figure 1-3 below shows the architecture of a Wireless Sensor Network that utilizes Cognitive Radio and DSA. It is important to note that some of the WSN and IoT networks will demand stringent performance metrics to deliver highly reliable services in critical situations.

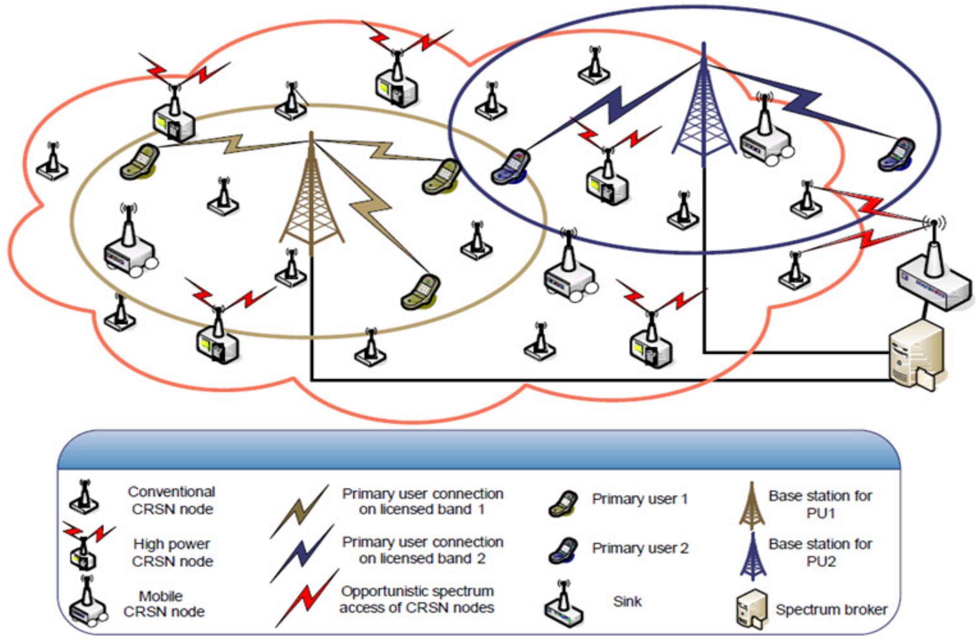

Figure 1-3: High Level Architecture of a Cognitive Radio Wireless Sensor Network [10]

Considerable work has been done to study spectrum utilization in the GSM frequency band and encouraging results for CR have been obtained. A study carried out in Kampala, Uganda on GSM 900 frequency occupancy in 2015 shows that the highest spectrum utilization is only 52.4 percent [5]. Another spectral occupancy measurement campaign carried out in Pune, India between February 2011 and March 2012 under various indoor and outdoor scenarios also concluded that the GSM 900 and 1800 bands are underutilized [11]. A report by the Spectrum Policy Task Force (SPTF) in the United States also shows that some cellular frequency bands remain largely unoccupied during the night up until morning [7]. For example, Figure 1-4 illustrates spectrum occupancy pattern for a 22 hour period (November 16 2005) on the 902-928Mhz band in Chicago and Illinois.

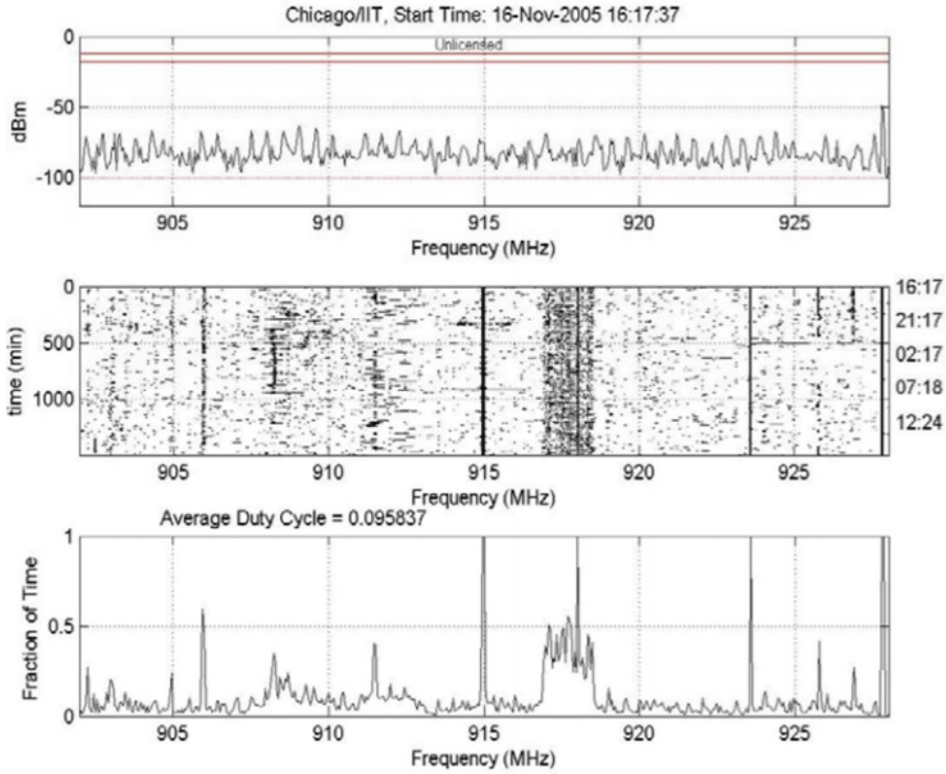

Figure 1-4: Spectrum Occupancy Measurements, Chicago and Illinois November 2005[6]

Spectrum occupancy measurements and campaigns only serve to demonstrate and allow understanding of the availability of spectrum opportunities, but play no role in the provisioning of spectrum for wireless services. However, through spectrum opportunities shown by these results, I have been motivated to examine and understand how different spectrum sensing techniques in cognitive radio can be used to exploit these opportunities and make an assessment on their performance.

1.3 Problem Statement

Cognitive Radio technology should be able to address problems of spectrum scarcity and underutilization in real world wireless applications. As such, the study of spectrum sensing techniques must consider and take into account the propagation effects on the wireless signal transmission including multipath, reflection, shadowing and fading, which are best modelled by a Rayleigh fading channel. It is crucial to ensure that CR designs behave consistently with test-bed simulations when deployed in the real environment.

The performance of spectrum sensing techniques, based on the Additive White Gaussian Noise channel is investigated in [12] and [13]. Studying and designing experiments to simulate and measure the behaviour of spectrum sensing techniques through the AWGN channel model may not present an accurate picture of their performance in some practical environments such as an urban area. Work in [14] investigates collaborative spectrum sensing for opportunistic access in fading environments and [15] proposes an efficient linear cooperation framework for spectrum sensing, where the global decision is based on simple energy detection over a linear combination of the local statistics from individual nodes. In furtherance to works available in literature on spectrum sensing in fading environments, this dissertation seeks to investigate the Rayleigh channel model characterisation of spectrum sensing techniques, to gain a better insight into their performance through real world, practical radio signals propagation environments.

1.4 Objectives

The main objective of this work is to analyse and evaluate the performance of different spectrum sensing techniques in a cognitive radio. The dissertation work considers the practical environment in which a cognitive radio operates, and thus evaluates the performance of the spectrum sensing techniques under Rayleigh fading channel model conditions. From this main objective, the following sub-objectives are derived.

1.4.1 Sub-objectives

i. Review the operation of wireless sensor networks in the unlicensed spectrum bands. This includes an analysis of how the performance of these networks is adversely affected by spectrum overcrowding and highlighting the increasing requirements for a paradigm shift in spectrum allocation policies.

ii. Design a software generated primary transmitter signal in MATLAB. This signal will have GSM 900 carrier frequency and modulation characteristics.

iii. Design and write MATLAB code to simulate the performance of Energy Detection spectrum sensing technique through a Rayleigh fading channel under varying SNR values.

iv. Design and write MATLAB code to simulate the performance of Matched Filter spectrum sensing technique through a Rayleigh fading channel under varying SNR values.

v. Design and write MATLAB code to simulate the performance of Cyclostationary feature spectrum sensing technique through a Rayleigh fading channel under varying SNR values.

vi. Evaluate the performance of the three spectrum sensing techniques based on ROC curves, complementary ROC curves and probability of detection vs signal-to-noise ratio.

vii. Demonstrate how energy detection based co-operative spectrum sensing techniques help in eliminating the so-called 'hidden node' problem phenomenon, which often encountered with individual receiver spectrum decisions.

1.5 Dissertation Overview

This section outlines the layout of the rest of this dissertation and provides a brief summary of the steps taken in each of the chapters in addressing the main objective of this project.

Chapter One

This chapter begins with a discussion on the challenges faced by IoT and other wireless telecommunication networks and applications due to frequency spectrum scarcity. The chapter highlights how the efficient use of available spectrum in both licensed and unlicensed bands, through dynamic spectrum access and cognitive radio will be key to the success of these technologies. Secondly, the chapter provides a brief background and motivation to this project in terms of how previous spectrum occupancy studies have overwhelmingly demonstrated the existence of spectrum white spaces, which can be opportunistically exploited through cognitive radio technology. The chapter then elaborates the problem statement and introduces the cognitive radio spectrum sensing techniques considered in this study. Finally, the chapter outlines the main objectives of this dissertation, together with a breakdown of the sub-objectives developed in addressing the problem statement.

Chapter Two

Chapter 2 covers the relevant literature review of cognitive radio technology and related concepts. A discussion of the background of cognitive radio is made, with a description of the cognitive cycle and the enabling cognitive radio techniques for dynamic spectrum access. An introduction to spectrum sensing techniques and their classification follows, with a detailed explanation of the conventional spectrum sensing techniques namely matched filter detection, cyclostationary feature detection and energy detection, and their mathematical derivations. The chapter also reviews co-operative spectrum sensing techniques based on energy detection. We conclude with a discussion of co-operative spectrum sensing techniques and the various approaches in which co-operative spectrum sensing can be implemented, and the related work available in literature.

Chapter Three

This chapter presents the methodology and system models for evaluating the proposed spectrum sensing techniques performance. We begin by revisiting the sub-objectives of the project, outlining the expected results. A presentation of the system model and binary hypothesis, used to analytically determine the presence or absence of a wireless signal follows. The chapter discusses and explains in detail the performance metrics that form the basis of spectrum sensing technique performance evaluation. A presentation for each spectrum sensing technique, and the mathematical derivations and their application to the system model in the performance evaluation follows. After presenting the system models, the chapter then outlines the project phases and the framework used from conception, design and testing. Figure 1-5 below illustrates the waterfall methodology model used in this project.

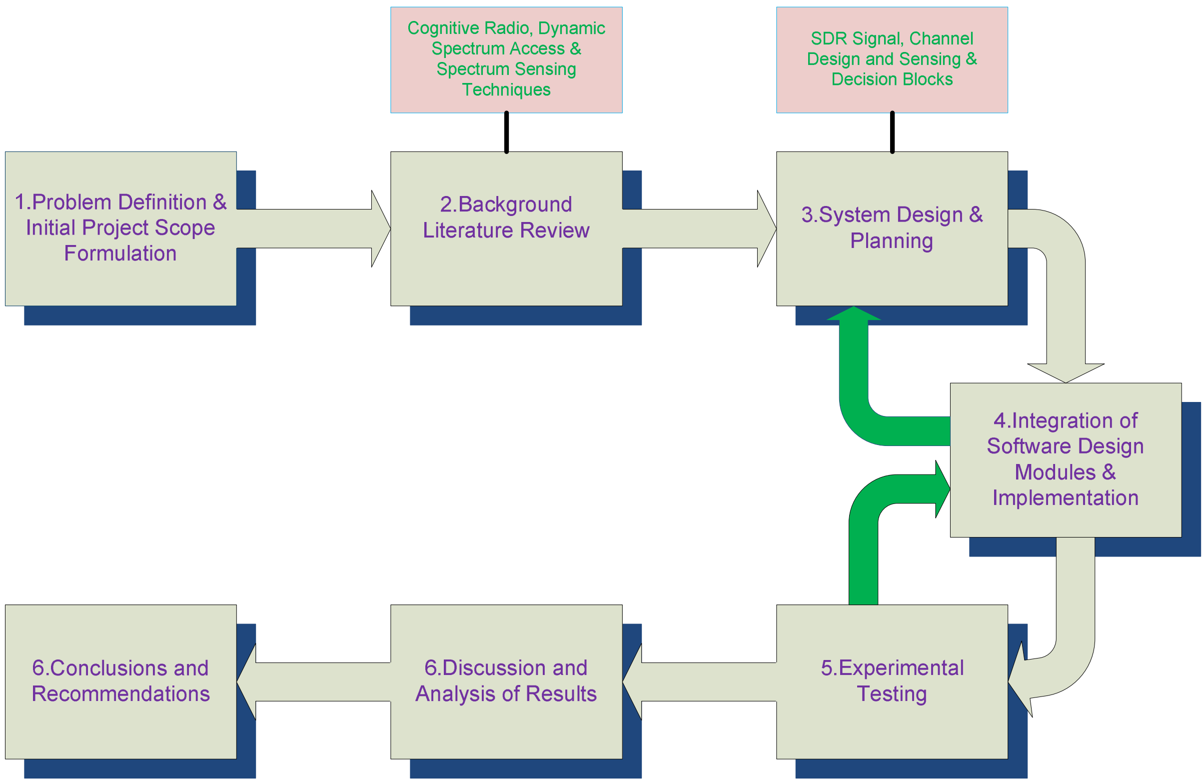

Figure 1-5: Overview of the project methodology

Chapter Four

Chapter Four presents the system design and implementation for performance assessment of the proposed spectrum sensing techniques by way of MATLAB simulations. To meet the main objectives, the design breaks down the system into software modules consisting of the SDR signal, convolution encoder, transmitter, Rayleigh fading channel, spectrum sensing algorithm and spectrum sensing decision block. Finally, a presentation of the integration of software modules and the implementation of the project in MATLAB is made.

Chapter Five

Chapter Five discusses MATLAB experimental results for the implementation of designs for each of the spectrum sensing techniques considered in this study. We then present a detailed analysis and compare the results for these spectrum sensing techniques, and seek to establish the relationship between environmental factors to the spectrum sensing performance levels.

Chapter Six

The final chapter of this dissertation discusses conclusions drawn from this study. These conclusions are based on MATLAB simulation results of the spectrum sensing techniques performance, and are compared to the project objectives presented in Chapter 1 to measure and ascertain if the objectives were met. We conclude with a discussion of future work that may be done to gain further insight into the performance of spectrum sensing techniques.

CHAPTER TWO

2 LITERATURE REVIEW

This chapter presents a comprehensive and detailed discussion of the fundamental aspects of the concept of cognitive radio, with respect to spectrum sensing. The focus is to first present an umbrella view of cognitive radio, before exploring a much deeper understanding of spectrum sensing techniques, focusing mainly on the ones that are subject to this study. Taking cognisance of the research gap that I intend to address through this study, a thorough review of both conventional and advanced spectrum sensing techniques available in literature is made. Figure 2-1 below is a visualization of the structure of this literature review. It begins with a brief account of the background of cognitive radio, followed by a discussion of dynamic spectrum access in cognitive radio and the cognitive radio cycle.

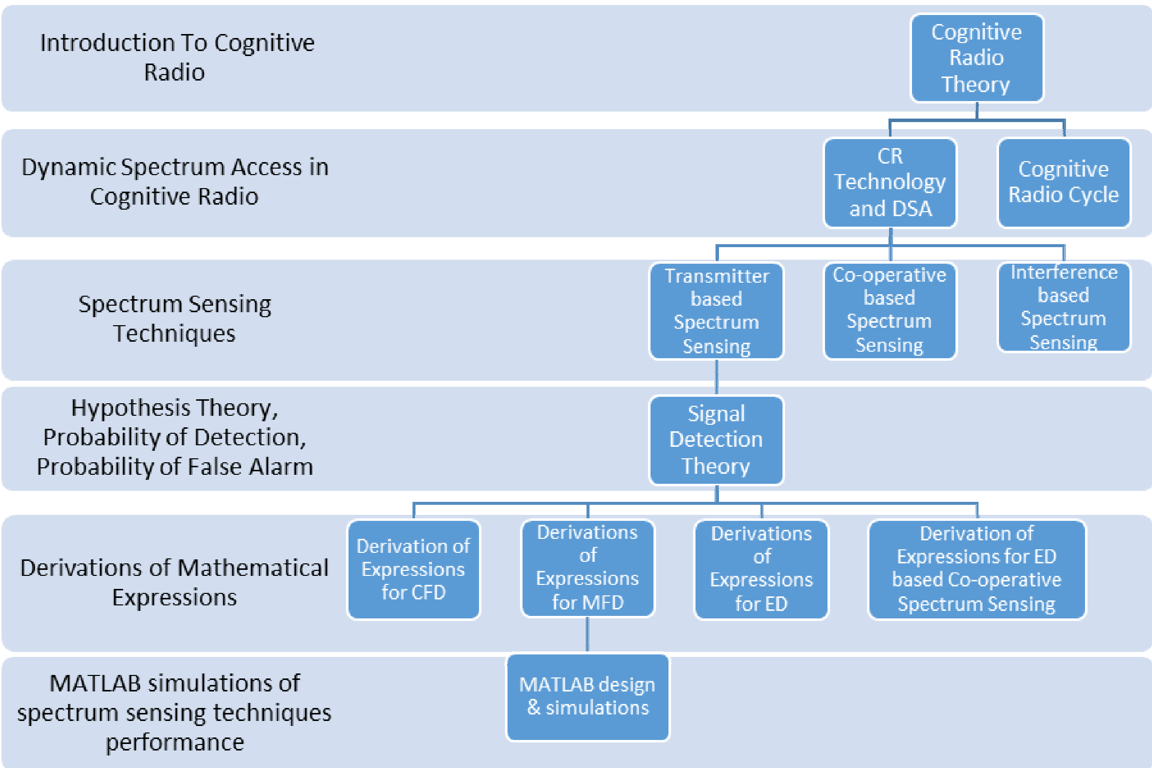

Figure 2-1: Literature Review Structure of the Spectrum Sensing Technique Evaluation project

2.1 Cognitive Radio

Joseph Mitola III described cognitive radio as the intersection of wireless personal technology and computational intelligence. He further asserted that it is the point at which wireless personal digital assistants (PDAs) and the related networks are sufficiently computationally intelligent about radio resources and related computer-to-computer communications to detect user communications needs as a function of use context, and to provide radio resources and wireless services most appropriate to those needs [16]. Cognitive radio is a newly developed technology that aims to enhance spectrum utilization and network efficiency [17]. As such, cognitive radio technology is an attempt to close the gap between the inefficient use of spectrum due to the fixed allocation policy, and the surging spectrum demand caused by the proliferation of new wireless applications. Cognitive radio foundation is premised on allowing unlicensed users or secondary users access to licensed spectrum holes in both the time and spatial domains, when primary users or licensed users are not active.

The architectural framework of a cognitive cycle block incorporates spectrum sensing, where secondary or cognitive users detect the presence or absence of primary (licensed) users transmission and opportunistically transmit in those idle spaces [18]. Radio parameters monitored in a cognitive radio include waveform, protocol, operating frequency and networking. Accordingly, if a licensed user has data to transmit, the secondary user is required to expeditiously vacate the spectrum resources in such a manner that guarantees minimal interference to the primary user transmission. A cognitive radio executes its functions through a set of organized, sequential and integrated phases referred to as a cognitive cycle.

2.1.1 Cognitive Cycle

The set of activities that a cognitive radio executes to effectively perform its function is known as the cognitive radio cycle. The cognitive cycle depicts how a cognitive radio systematically responds to external stimuli in the form of radio transmissions within the environment it operates, as shown in Figure 2-2 below [19].

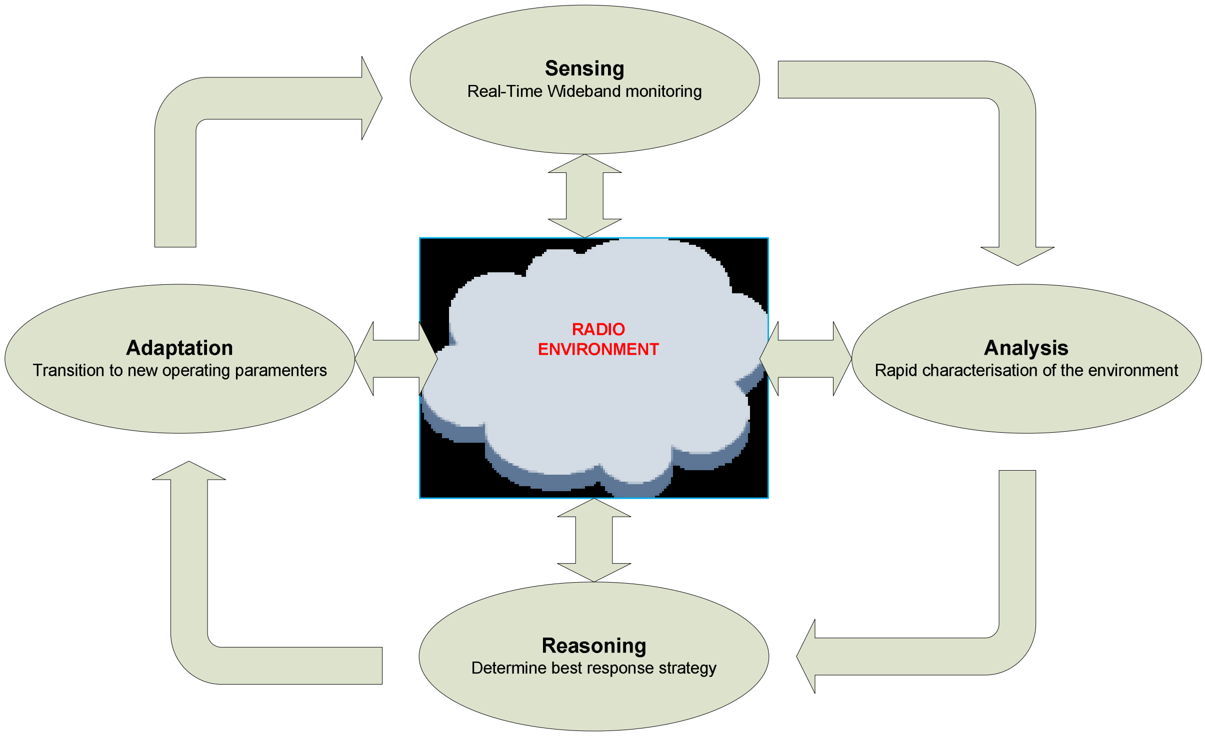

Figure 2-2: Simplified block diagram of a Cognitive Radio Cycle[19]

The cycle begins with the sensing and observation state, where the radio observes and monitors its RF environment. During spectrum sensing, the CR continuously observes the RF environment so that it becomes aware of the fundamental parameters of the wireless channel as well as the availability of wireless spectrum [20]. The next stage of the cycle is spectrum analysis. Based on the spectrum sensing results, spectrum analysis incorporates several factors in the external and internal radio environment in order to determine the optimal communication protocol, channel frequency and transmission power. The final phase of the cognitive cycle is spectrum decision making. Based on the outcome of spectrum analysis the CR makes a decision whether spectrum resource is available or not.

The CR may also decide if it is appropriate to reconfigure the transmission channel or medium access protocol to adapt to changing wireless environment. Spectrum decision making may also involve adjusting transmission power, changing the waveform or transmission parameters such as modulation and channel coding schemes.

The major goal of Cognitive Radio technology is to improve efficient use of spectrum by allowing secondary users to opportunistically access licensed spectrum without causing harmful interference to the licensed users. Ultimately, this minimizes interference whilst at the same time increasing traffic density. New generation wireless communication systems require very reliable spectrum sensing algorithms to enhance better performance through improved resource management. Dynamic spectrum access is a key component in the realisation of cognitive radio and allows devices to sense and identify gaps in the spectrum known as white spaces and put them to use.

To emphasize the importance of DSA in CR, the next section provides an insight into the role of dynamic spectrum access and the fundamental spectrum sensing techniques utilised in identifying spectrum opportunities.

2.1.2 Cognitive Radio Techniques For Dynamic Spectrum Access

Worldwide, the current spectrum management strategy emanates from techniques employed during the early days of broadcast radio, where there was no regulation management and broadcasters resorted to increasing power levels as a way of competing with rivals. Due to high interference levels, regulatory bodies to manage fair usage of spectrum were formed and these divided frequency bands and assigned them for use on a license basis. Fixed and wireless communication services followed the same regulation philosophy to manage interference and orderly use of the spectrum resource. In spite of administrative control of spectrum usage to combat interference, spectrum studies carried worldwide reveal that licensed exclusive rights usage of spectrum exhibit underutilization in most allocated bands [5]. Generally, there is consensus in both academia and industry that static spectrum allocation is partly responsible for the problem of spectrum scarcity encountered today.

Clearly, a more flexible, measurement driven regulation strategy that allows devices to autonomously monitor frequency occupancy and exploit vacant pockets in the spatio-temporal domain may lead to improved efficiency in the use of spectrum resource. To this end, in order to improve spectrum efficiency, one of the most recent trends is the development of Dynamic Spectrum Access Networks (DSANs).

Dynamic Spectrum Access is defined as a technique by which the operating spectrum of a radio network can be selected dynamically from the available spectrum [22]. For example, in cellular networks, advances in technologies such as reconfigurability, adaptive radio, software defined radios and multi band radio in end user devices have made dynamic spectrum access in cellular networks feasible. Dynamic Spectrum Access in cellular networks such as CDMA and GSM uses a regional spectrum broker that controls time-bounded spectrum access through the use of a dynamically shareable spectrum band and a concept known as statistical multiplexed access, to achieve better spectrum utilization [23]. Dynamic spectrum access is also considered an attractive prospect in wireless sensor networks. Most WSN operate in unlicensed spectrum bands, also used by other unlicensed devices such as IEEE802.11 wireless local area networks (WLAN) hotspots, PDAs, Bluetooth and ZigBee devices. Therefore wireless sensor networks experience spectrum overcrowding and to enhance performance, opportunistic spectrum access schemes must be used [10].

2.2 Spectrum Sensing Techniques

To accommodate spectrum demands for emerging wireless technologies and applications, current research is now driving towards the development of instruments and methodologies that make it feasible to exploit underutilized spectrum resources in the time, frequency and spatial domains as shown in Figure 2-3.

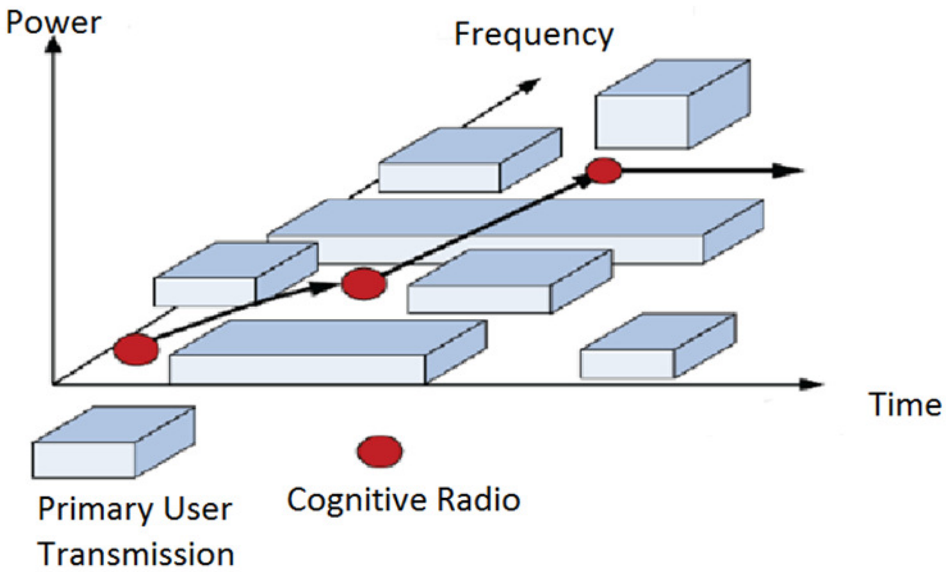

Figure 2-3: Illustration of time and frequency domain spectrum opportunities [24].

As these new applications emerge, business cases have been thoroughly examined and technologies such as adaptive smart antennae, adaptive radio concepts and improved efficient use of the spectrum explored, to support continued growth of the revenue streams. Cognitive radio networks are being developed to boost spectrum utilization by granting unlicensed users rights to use licensed spectrum. In a cognitive radio function, it is critical that spectrum opportunities are timely and accurately detected by the secondary user. If a primary transmission is detected when in fact the primary user is idle, this scenario translates to a missed opportunity by the secondary user to transmit its data. If the secondary user fails to detect a primary user transmission and transmits at the same time, this will result in interference and service degradation. It is thus imperative to understand the role of spectrum sensing in a cognitive radio. By definition, spectrum sensing is the task of collecting spectrum information regarding spectrum resource utilization in a given geographical area and this information is used to accommodate secondary users on a non-interfering basis[25]. To that end, a number of spectrum sensing techniques have been proposed and studied to identify spectrum opportunities in a scanned spectrum band. Broadly, these are classified into three categories namely Transmitter detection based, interference based and co-operative detection as shown in Figure 2-4.

Transmitter based detection comprises energy detection, cyclostationary feature and matched filter detection [26].

Depending on whether these techniques possess any partial, complete a priori knowledge of the transmitter or not, they are further classified as semi-coherent, coherent or non-coherent respectively [27]. Co-operative spectrum sensing aggregates sensing information from a number of CR nodes in order to achieve a more accurate detection with respect to the status of the primary user [28]. Interference based spectrum sensing is a form of underlay spectrum sharing, where the CR transmits at the same time as the primary user, but observes a specified interference threshold referred to as the interference temperature limit [29].

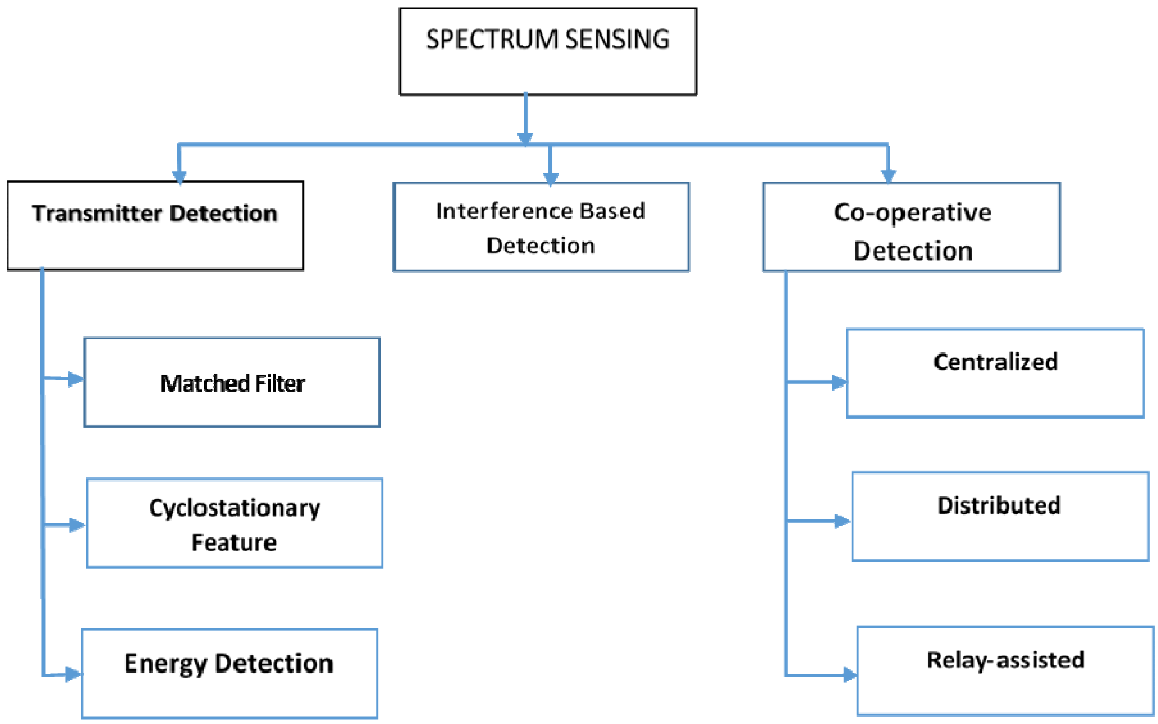

Figure 2-4: Classification of spectrum sensing techniques.

2.2.1 Transmitter- based Detection Techniques

Transmitter-based detection techniques rely on local measurements and observations to detect the presence of primary user transmission [30]. The detection model is purely based on analysis of the received signal at the secondary user receiver end. In transmitter-based detection, the aim is to find primary users operating at a given time within the secondary user's neighbourhood, using local measurements and observations. The SU examines the signal strength generated from the PU and exploits partially, or in full, the vacant sub bands within the channel.

Analytically, the decision on the availability of primary user transmission is reduced to a statistical detection problem. This is characterised as a hypothesis test stated below.

$$x(k) = \begin{cases} n(k) & : H_0 \\ hs(k) + n(k) & : H_1 \end{cases} \qquad (2.1)$$

where ***x(k)*** represents the sample to be analysed at instant ***k***, ***h*** denotes the channel gain, ***s(k)*** denotes the transmitted signal sample at instant ***k*** and ***n(k)*** denotes the sample noise of the channel at instant ***k***.

The probability matrix for the different scenarios and their possible outcomes is shown in Figure 2-5 below.

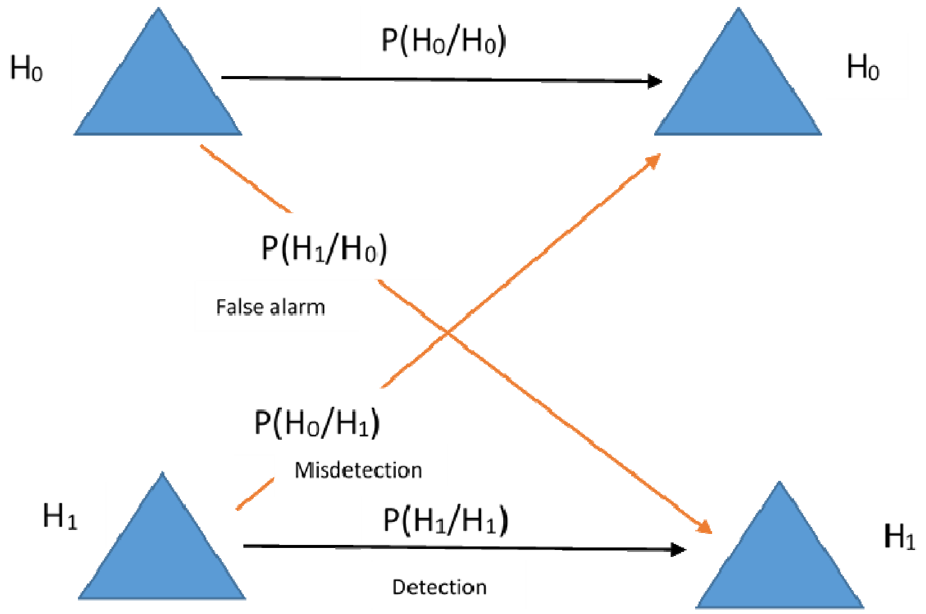

Figure 2-5: Possible outcomes and corresponding probabilities for the signal detection hypothesis test.

H_0 is the null hypothesis representing a sensed state where the primary signal is not present.

H_1 is the alternative hypothesis representing a sensed state where the primary signal is present in the spectrum band or sub band of interest.

Scenario 1: Declaring H_0 when H_0 is TRUE

Scenario 2: Declaring H_1 when H_0 is TRUE

Scenario 3: Declaring H_1 when H_1 is TRUE

Scenario 4 : Declaring H_0 when H_1 is TRUE

Scenario 3 represents a correct signal detection event, whereas scenario 2 and scenario 4 represent a false alarm and a misdetection respectively. The probability of declaring the presence of a primary signal when there is no primary signal as represented by scenario 2 is known as the probability of false alarm. On the other hand, the probability of declaring that there is no primary user transmission when the primary user signal is present as represented by scenario 4 is known as the probability of misdetection. The probability of detection represented by scenario 3 means primary user transmission has been correctly detected.

A cognitive radio equipped with an ideal spectrum sensing technique will detect primary user transmission all the time. This is however, not possible due to environmental factors and statistical noise uncertainty. It is imperative that a spectrum sensing technique achieves minimum performance levels specified by some statistical metrics, that is probability of detection, probability of miss and false alarm. In particular, a higher probability of miss implies a higher likelihood of causing interference perceived by primary user transmission. Similarly, a higher probability of false alarm is unacceptable, as it would result in numerous missed spectrum opportunities and hence poor spectrum utilization. Different frequency bands experience different propagation characteristics. Consequently, design of detection algorithms and the analysis of associated performance is a challenging task.

2.2.1.1 Energy Detection

In energy detection techniques, the primary user transmission detection is based on the analysis of signal energy level in the band of interest, over a specified time duration. Precisely, the signal is detected by comparing the energy output of the energy detector to an appropriately selected threshold determined by the noise floor [31]. Energy detection does not require any channel gains, other parameter estimates and any prior knowledge of the primary signal. Energy detection spectrum sensing is thus particularly attractive due to its low complexity and cost [22].

The principle of energy detection hinges on the assumption that the energy level of the signal is always higher than the noise energy level. Suffice to say, the key parameters used in energy detection technique include the detection threshold value, number of samples and estimated noise power.

Theoretically, two models for the energy detector are used in time domain implementations, namely the analogue and digital energy detector. The analogue energy detector consists of a pre-filter followed by a square law device and a finite time integrator. The role of the pre-filter is to band limit the noise bandwidth and normalise the noise variance.

The analogue and digital energy detector implementations are shown in Figure 2-6. The digital energy detector consists of a low pass noise pre-filter, an analogue to digital converter followed by a square law device and a finite integrator.

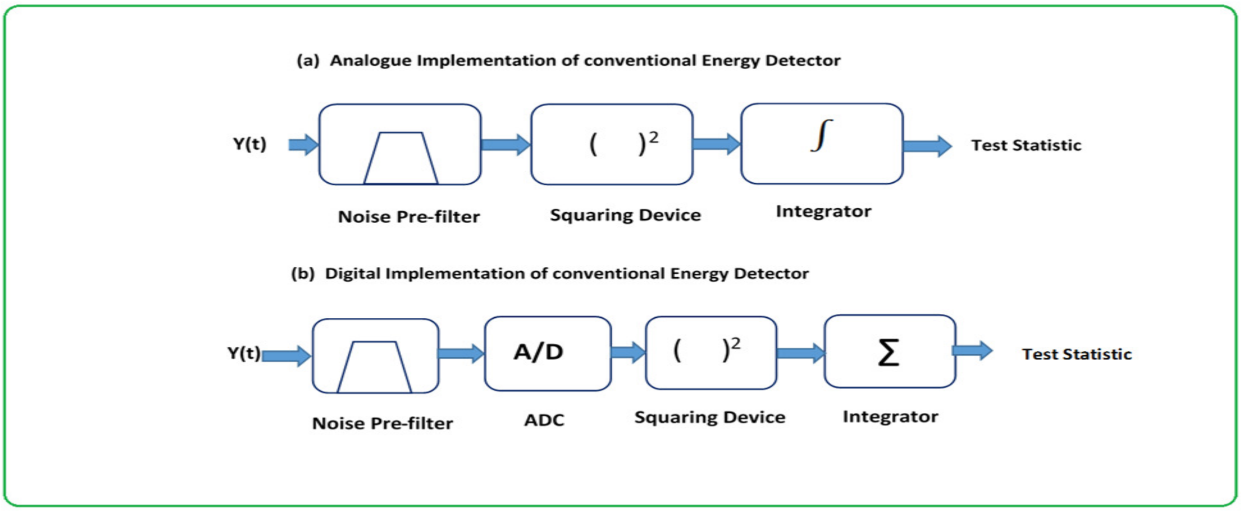

Figure 2-6: Analog and Digital implementation of the conventional energy detector [31]

The main parameters considered in the design of energy detector are the threshold value and the number of samples. Although the signal to noise ratio (SNR) and noise variance determine the performance of energy detector, practically, designers have no control over these parameters as they depend on the wireless channel environment.

To decide whether a primary user is present or not, a pre-determined threshold value is required. The threshold value has a direct bearing on all performance metrics including the probability of detection denoted by $\mathbf{P_d}$, probability of false alarm denoted by $\mathbf{P_{FA}}$ and probability of misdetection denoted by $\mathbf{P_{MD}}$. The selection of the threshold can be done based on the target of the performance metric of interest [22].

The number of samples is also a critical design parameter of the energy detector. Energy detector is the most optimal method when the signal is not deterministic and only the average power of the signal is known.

The detector can be expressed mathematically as [32]:

$$D(Y) = \frac{1}{N}\sum_{n=0}^{N-1}[X(n)]^2 \qquad D(Y) > \boldsymbol{\gamma} : \boldsymbol{H_1} \text{ and } \boldsymbol{H_0} \text{ otherwise} \tag{2.2}$$

Where Y is the average power of the received signal, *D(Y)* is the decision variable, that is deciding if the primary signal is present or not, *N* is the number of samples and $\boldsymbol{\gamma}$ is the decision threshold. X(n) is the transmitted signal from the primary user.

If the noise floor, and hence the noise variance is completely known, then by the Central Limit Theorem [22], the distribution of the decision variable approximates to a normal distribution.

$$D(Y|H_0) \sim N\left(\sigma_n^2, \frac{2\sigma_n^4}{N}\right) \tag{2.3}$$

$$D(Y|H_1) \sim N(P + \sigma_n^2, \frac{2(P + 2\sigma_n^4)^2}{N})) \tag{2.4}$$

Where σ_n^2 is the noise variance and P is the primary signal power.

The expressions for the probabilities of detection and false alarm are given as follows:

$$P_{fa} = Q\left(\frac{\gamma - \sigma_n^2}{\sqrt{(2\sigma_n^4/N)}}\right) \tag{2.5}$$

$$P_d = Q\left(\frac{\gamma - (P + \sigma_n^2)}{\sqrt{\frac{2(P+\sigma_n^2)^2}{N}}}\right) \tag{2.6}$$

Reducing equation 2.5 and 2.6, we can deduce the relationship between the number of samples N, the signal to noise ratio, SNR, probability of detection P_d and probability of false alarm P_{fa}, as shown in 2.7 below. The signal to noise ratio is defined as the ratio of the signal power to the noise power.

$$N = 2\left[Q^{-1}\left(P_{fa}\right) - Q^{-1}(P_d)\right]^2 (SNR)^{-2} \qquad (2.7)$$

A comprehensive investigation on the effect of the number of samples on detection performance is outlined in [32]. This approach assumes the signals are deterministic in nature and exists over a flat band-limited Gaussian noise channel with noise variance a known priori. A further assumption is that noise power should be known, which is not possible as it depends on propagation channel environment. A minimum threshold should be calculated based on the worst-case noise scenario, thus making it necessary to have a sensitive signal detector. Work in [32] analyses energy detector spectrum sensing algorithms for various parameters including SNR, number of samples and noise uncertainty. By varying the P_{fa} from 0 to 0.9 and fixing the SNR, results show that the P_d increases with the number of samples N. This analysis is however, a time domain analysis and do not consider the spectral components of the signals.

In recent times, several modifications to the classical energy detector approach have been proposed in literature. The energy detector sensing performance based on an estimated noise floor degrades at low SNR. Consequently, work in [33] addresses this problem by proposing a double threshold based spectrum sensing which considers sensing history in confusion regions. The test statistic is compared to the two thresholds and a decision on spectrum availability made accordingly. If the test statistic is higher than the upper threshold, spectrum is considered unavailable. Contrarily, if the test statistic is lower than the lower threshold, spectrum is considered unoccupied. If the test static lies between the lower and upper threshold values (confusion region) re-sensing is performed iteratively until a clear decision on spectrum availability is reached. This approach improves the overall performance of the detector compared to a single threshold approach. However, in cases where the test statistic lies in the confusion region and re-sensing is required, it increases the spectrum sensing delay.

Another study that seeks to boost energy detection spectrum sensing at low SNR, uses an adaptive threshold model and is presented in [34]. Work in [35] proposes a cubing and double-squaring operation on the conventional energy detection technique, and reports that detection performance for AWGN channel improves by 1.3 times, whilst detection performance for Rayleigh fading channel improves by 0.5 times.

2.2.1.2 Cyclostationary Feature Detection

A signal that exhibits statistical attributes, such as mean and autocorrelation, that vary periodically with time is said to possess cyclostationary features. Cyclostationary processes are random processes for which the statistical properties such as mean and autocorrelation change periodically as a function of time[36]. Cyclostationary Feature detection exploits cyclostationary properties inherent in wireless signal transmissions, with periodic statistics and spectral correlation that cannot be found in any interfering signal or stationary noise [37].

It utilizes this periodicity in the received signal to identify the presence of the primary signal. Most wireless communication signals exhibit cyclostationarity, encapsulated as periodicities in the signal structures depending on their data rate, modulation types and carrier frequencies. For example, the identification of a unique set of characteristics particular to a radio signal on the air interface can be used to detect the signal based on its cyclostationary features.

Because cyclostationary feature detection exploits periodicity statistics and spectral correlation not found in stationary noise and interfering signals, the method has high noise immunity compared to other spectrum sensing methods.

Many of the signal processing techniques used in the analysis of noise contaminated communication signals employ probabilistic models based on cyclostationary features. Consequently, the theory of cyclostationary feature detection conceptualises the fact that several man-made signals possess hidden periodicities, which can be regenerated by a sine wave extraction method, thus producing features at frequencies that depend on the built in periodicities.

A zero mean continuous time signal *x(t)* is said to be wide sense cyclostationary if it satisfies the following conditions [38]:

$$m_x(t) = E[x(t)] = m_x(t + mT_0) \tag{2.8}$$

$$R_x(t,\tau) = R_x(t + T_0, \tau) \tag{2.9}$$

where T_0 is the period of the signal, τ represents the time offset, E(·) is the signal mean, $R_x(t,\tau)$ is the autocorrelation function of $x(t)$.

As the auto-correlation function is periodic, its Fourier series $R_x^\alpha(\tau)$ can be defined as follows:

$$R_x^\alpha(\tau) = \frac{1}{T_0} \int_{T_0} R_s\,(t,\tau) e^{-2j\pi\alpha\tau}\, d\tau \tag{2.10}$$

where $R_x^{\alpha}(\tau) = \lim_{T_0 \to \infty} \frac{1}{T_0} \int_T x\left(t - \frac{\tau}{2}\right) x\left(t + \frac{\tau}{2}\right) \exp(-2\pi j \alpha t)\, dt$ (2.11)

Equation (2.11) is referred to as the cyclic auto-correlation function and every signal characterised by a cyclostationary process with period T_0, the function is non-zero at $\alpha = 1/T_0$. Contrarily for a stationary process such as noise, the function is zero-valued. Applying the Wiener relationship, that is taking Fourier series representation with respect to τ, we obtain the cyclostationary spectrum density function CSD, or the spectral correlation function SCF, whose evaluation leads to:

$$S_x^{\alpha}(f) = \lim_{\tau \to \infty} \int_{-\tau}^{\tau} R_x^{\alpha} \exp(-2\pi j f \tau)\, d\tau \qquad (2.12)$$

Function (2.12) is an expression in the frequency domain with two variables, the spectral frequency and the cycle frequency than can be used to detect cyclostationary feature. More so, unique non-zero cyclic frequencies can thus be used to identify different primary signals.

A simplified version of the SCF function (2.12) is given as in (2.13) for ease computation [39].

$$S_x^{\alpha}(f) = \lim_{T \to \infty} \frac{1}{T} \int_{-T/2}^{T/2} X_{T_0}\left(t, f + \frac{1}{\alpha}\right) X_{T_0}'\left(t, f - \frac{1}{\alpha}\right) dt \qquad (2.13)$$

In (2.13), the term X_{T_0} is the short time Fourier Transform of $x(t)$ with bandwidth $\frac{1}{T}$ and $X_{T_0}'(t,f)$ is the complex conjugate of $X_{T_0}(t,f)$ expressed by:

$$X_{T_0}(t,u) = \int_{t-T/2}^{t+T/2} x(u) \exp(-2\pi j f u)\, du \qquad (2.14)$$

The function in (2.13) is known as the time smoothed Spectral Correlation Function and theoretically achieves true SCF under the condition $T >> T_0$. Plotting the SCF function can be used to establish the occupancy status of the spectrum by observing the peak at the centre of the operating frequency presented by the SCF. If there is no peak at the centre, it implies there is no primary signal transmission in the band of interest.

Compared to matched filter detection, cyclostationary feature detection does not require close synchronisation and perfect knowledge of the waveform of the signal of interest, phase or frequency synchronisation, making it suitable in cases where this knowledge is unknown. Additionally, this method has strong performance under low SNR as noise signals are random signals with no form of periodicity.

A number of studies on using cyclostationary feature detection are available in literature. The authors in [36] investigate the problem of detecting vacant spectrum bands for an 802.11a signal using cyclostationary feature extraction and outline approaches for detection using cyclostationary signatures. The cyclic spectrum is estimated using the FFT Accumulation Method (FFM), which is based on the modifications of time smoothed cyclic cross periodogram mentioned in (2.13). Results show very good performance of the CFD under low SNR conditions.

A prominent problem with the use of SCF in estimating and identifying primary user transmission is the requirement for an extremely high sampling rate, which leads to high computational complexity. In practical implementations, the number of observation samples is limited such that the PU signal and noise in the received signal are not completely uncorrelated introducing significant levels of performance degradation. To address this problem, authors in [40] propose a novel approach that applies the low-rank and sparse decomposition technique to cyclostationary feature based spectrum sensing. This approach decomposes the spectrum function matrix into two matrices, with the low ranking matrix representing noise and interference signals whilst the sparse one represents the cyclostationary feature in the primary user signal. Analysis of results for this novel approach show that it achieves performance levels better than conventional energy detection and cyclostationary feature.

Another proposal for improving cyclostationary feature spectrum sensing is presented in [38]. This approach uses an algorithm based on CFD and Hilbert transformation to improve detection in complicated electromagnetic environments. Simulation results indicate that this approach can be used to detect both simple signals and modulated cyclostationary signals, and yield satisfactory performance compared to conventional energy detection algorithm. In [41] the authors propose a new CFD approach that is based on the correlation between signal and noise for detection of OFDM based primary users. The proposed scheme aims to improve the noise robustness through optimal utilization of the information in the cyclic spectrum of the received signals. The signal is first subjected to signal processing techniques to reduce noise and to change the cyclic spectral density function into a gray scale. To provide a clearer feature, the signal is then passed through a Wiener filter to reduce the amount of noise. Simulation results for various modulation techniques that include FSK, PSK and ASK show that this approach outperforms conventional CFD in low SNR conditions.

Further work on the performance of CFD is outlined in [42][43][44] and is all aimed at optimising the performance of the conventional technique.

2.2.1.3 Matched Filter Detection

Apart from the CFD and ED spectrum sensing technique, Matched Filter Detection (MFD) method is another widely used spectrum sensing technique and is widely used when the characteristics of the primary signal such as modulation format, carrier frequency, order, pulse shape and packet format are known [45]. The matched filter is an optimal linear filter that is designed to maximize the signal to noise ratio in the presence of additive stochastic noise [46]. The known signal features are used to implement a MF when the primary signal has preambles, synchronization words or spreading codes that lead to coherent detection. In the frequency domain, the matched filter applies the weights of the spectral components that have the greatest SNR. In wireless communication, a MF is a correlation scheme between a known signal and an unknown signal to detect the presence of the known waveform in a transmitted signal. In signal processing, this is equivalent to convolving the unknown received signal ***x(t)*** with a conjugated time reversed version of the known signal [45]. A typical block diagram for a Matched Filter Detector is illustrated in Figure 2-7 below.

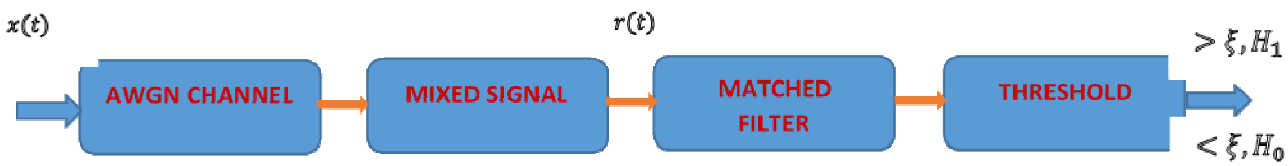

Figure 2-7: Typical Block Diagram of a Matched Filter

The operation of the matched filter detection is expressed as follows :

$$Y[n] = \sum_{K=-\infty}^{\infty} h[n-k]x[k] \qquad (2.14)$$

Where x is the unknown signal and is convolved 'h' the impulse response of the matched filter that is matched to the reference signal for maximizing the signal to noise ratio. The output of this operation is compared to a threshold factor ξ to determine the presence or absence of the PU.

The probability of detection and the probabilities of detection and false alarm for the MFD, according to the Neyman-Pearson criteria, denoted by P_d and P_f respectively, are given as follows [47]:

$$P_d = Q\left(\frac{\xi - E}{\sqrt{E\sigma_n^2}}\right) \tag{2.15}$$

$$P_f = Q\left(\frac{\xi}{\sqrt{E\sigma_n^2}}\right) \tag{2.16}$$

where $Q(.)$ is the Gaussian complexity distribution function, E is the energy of the deterministic signal of interest and σ_n^2 is the noise variance.

The biggest strength of MFD is its ability to detect primary signals in less time. On the other hand, MFD may obtain inaccurate detection results if the correct information about primary user is not adequately incorporated in secondary user design. A dedicated operation to detect each primary user technology is required at the secondary user end, which increases complexity and power consumption.

There has been considerable research work on MFD, primarily aimed at improving detection performance achieved by the conventional MFD. In [48] ,an adaptive detection threshold scheme, which attempts to maximize probability of detection for a given probability of false alarm is proposed. This scheme is motivated by some general observations on the response of the probability of detection and probability of false alarm as the detection threshold is varied. Specifically, it is observed that as the decision threshold is decreased, probability of detection increases and so does the probability of false alarm.

This has brought about a conclusion that the selection of the detection threshold should never be at the extremes (between zero and infinity). This proposal is implemented and simulated over AWGN channel for artificial neural networks.

In [49], the authors propose a matched filter detection scheme which, besides using the decision threshold to determine the presence of primary user, also takes into account the power levels of the primary user signal to achieve more cognition for Cognitive Radio. More work to study the performance of MFD is outlined in [47], [50] and [51].

2.2.2 Interference Based Detection

This spectrum sensing technique falls under underlay dynamic spectrum sharing and will not be investigated in this dissertation work. Nonetheless, a brief literature review of the technique is provided to consolidate an overview perspective of spectrum sensing.

In this model, the SU is allowed to transmit at the same time as the PU, but has to measure the interference environment to ensure that the interference does not go above a certain threshold defined by PU tolerance to interference [7]. The interference threshold is referred to as the interference temperature limit and is used as a bound for the interference caused to the licensed users in a particular frequency band at a particular location, as shown in Figure 2.8.

It is noteworthy that this technique is theoretical, and is premised on the measure of how well a radio operating within a particular modulation scheme and protocol can tolerate interference within its spectrum space. As the signal traverses the wireless channel, exponential propagation losses are encountered with distance from the source, continuously until it reaches the level of the noise floor [52]. From this minimum distance, the secondary user considers primary signal as noise, and can utilize the channel and transmit simultaneously. Above the maximum noise level, an interference cap is introduced and beneath this threshold, the primary receiver will treat this transmission as noise.

The major challenge faced with the practical implementation of this technique is the determination of the interference temperature levels for various wireless communication standards and protocols. . It would be a mistake for cognitive radios to make theoretical assumptions about the noise tolerance of radio channels without more specific knowledge of the devices in question [52].

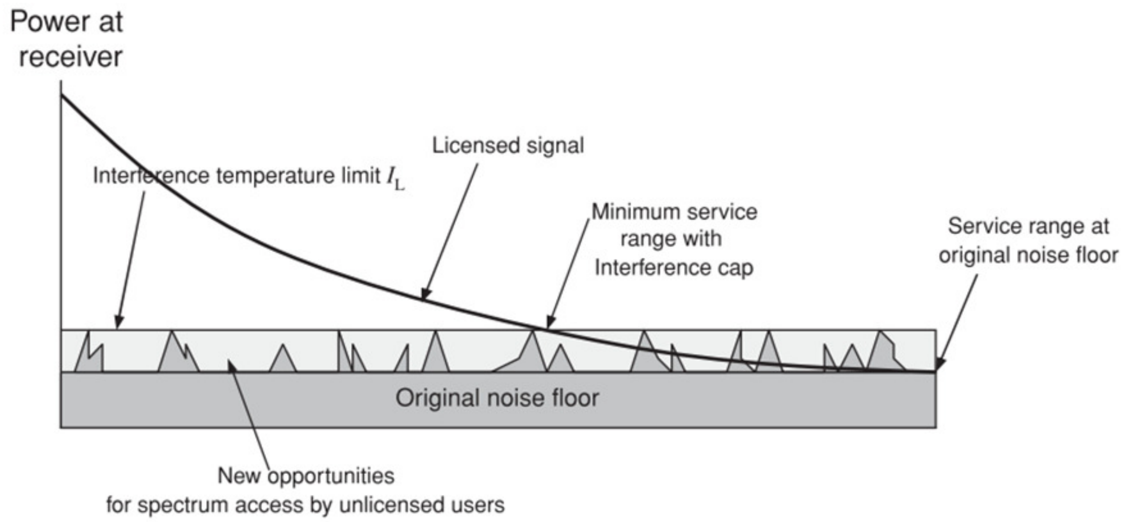

Figure 2-8: Illustration of the Interference Temperature Limit. Figure adapted from [7]

2.2.3 Co-operative Spectrum Sensing

One of the major challenges experienced by cognitive radio nodes in spectrum sensing is due to receiver uncertainty, multipath fading, shadowing and the hidden node phenomenon [28], shown in Figure 2-8. From literature, co-operation among CR nodes has been discussed as a possible solution to mitigate the aforementioned problems. In co-operative spectrum sensing, multiple secondary users (SUs) collaborate in a centralised or decentralised manner to determine the availability of spectrum holes for opportunistic access.

Each SU independently senses spectrum using any of the sensing algorithms previously described, and shares the sensing information with peer sensing nodes based on a selected strategy [53]. Co-operation among CRs has been shown to significantly reduce the probabilities of misdetection and false alarms.

As can be observed in Figure 2-9, CR1 and CR2 are within range of the PU transmission whilst CR3 is spatially positioned in such a way that it is out of reach of the PU transmission. Due to multipath signals and shadowing effects caused by obstructions, detection of primary transmissions by CR2 may be impaired. On the other hand, CR3 is unaware of PU transmission due to range factor and the presence of the PU receiver within range. As a result, transmissions of CR3 will cause interference to the PU receiver if it initiates transmission within the same frequency band and at the same time as the primary user.

However, exploiting the spatial diversity of the secondary users by enabling them to co-operatively share sensed data, the sensing accuracy can be significantly increased. This results from the fact that statistically, it is unlikely that all SUs spread in space will experience receiver uncertainty and shadowing at the same time.

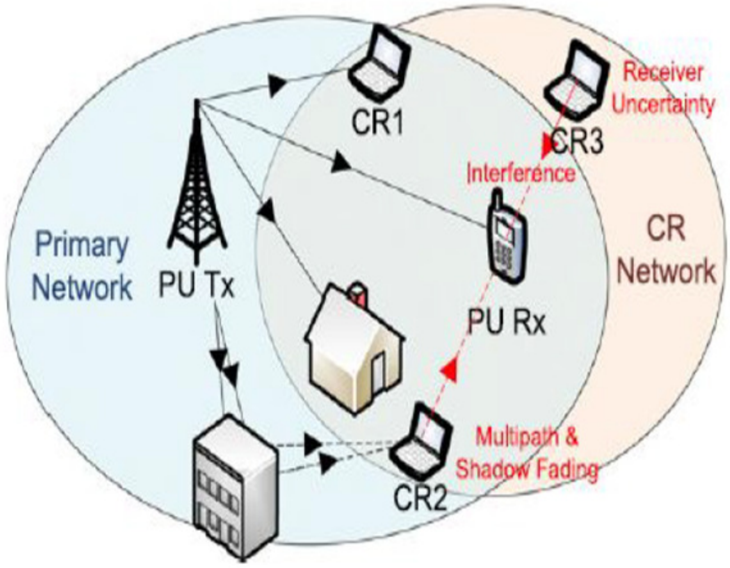

Figure 2-9: Illustration on how Receiver uncertainty, Multipath fading and shadowing and Hidden node phenomenon arises in Cognitive Radio [54]

There are two methods to model the co-operative spectrum-sensing scheme, namely the centralised node and distributed sensing approach, discussed in the following subsections. Local spectrum sensing data is shared amongst the co-operating nodes via the control or reporting channels [55].

2.2.3.1 Centralised Node Approach

In centralised node approach, SUs report their sensing data to a centralised node designated as the Fusion Centre (FC) or the base station (BS) [56], as shown in Figure 2-10. The Fusion Centre collates the sensing information from the co-operating nodes and makes a decision on the availability of spectrum opportunities. Centralised node approach adopts two methods in determining whether a spectrum hole is available or not. These are termed data fusion and decision fusion method. In data fusion, co-operating nodes send locally collected sensing data to the FC, allowing it to perform data fusion and make a centralised decision on the availability of spectrum, in a fashion known as soft combining. Alternatively, the co-operating nodes each sends individual decisions to the FC, which then performs decision fusion to reach spectrum decision, in a fashion known as hard combining fusion.

2.2.3.2 Distributed Node Approach

The distributed co-operation approach eliminates the need for a fusion centre by allowing CRs to exchange sensing measurements, using a pre-agreed algorithm, with their neighbours to make a decision about the status of the primary user transmission [57].

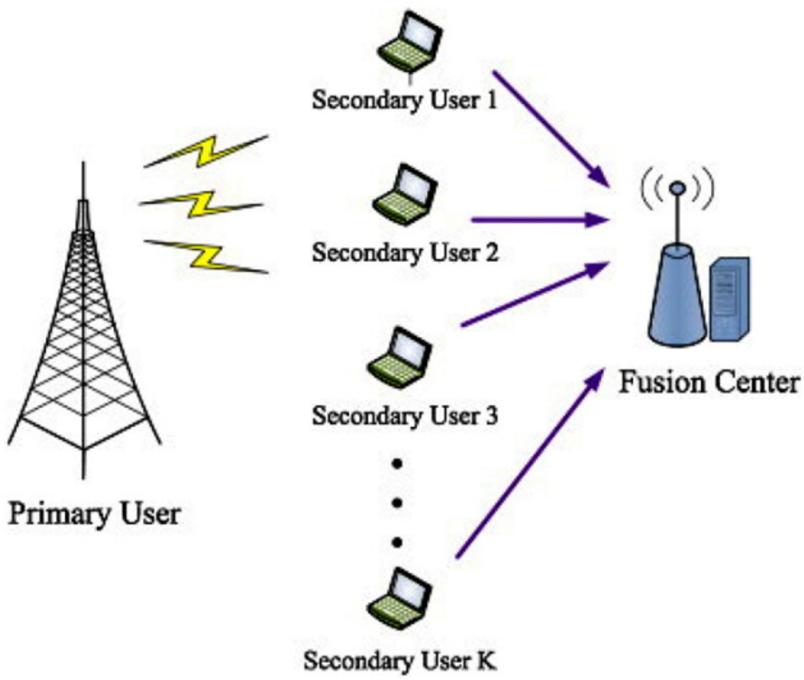

Figure 2-10: Centralised Co-operative Spectrum sensing Approach in Cognitive Radio

This pre-agreed sensing algorithm follows three steps. First, each co-operating node sends its sensing data to other CRs in the neighbourhood, usually defined by the transmission range. In the next stage, co-operating devices combine local data with the received sensing information from its neighbours to determine the presence or absence of primary user transmission based on a local criterion. It is worth noting that shared spectrum observations are in the form of soft sensing results of local decisions about spectrum white spaces availability. In a case where spectrum hole is not identified, this process is repeated iteratively until the scheme converges with a collective decision on spectrum availability achieved.

2.2.4 Research on Co-operative Spectrum Sensing

To date, a number of research efforts on co-operative spectrum sensing have been done and are available in literature. In [58], the authors have made a comprehensive survey on co-operative spectrum sensing techniques. Three hard combining approaches, the AND, OR and M out of K rules, where M is the number signal detections and K denotes the number of users transmitting their test statistic to the FC, are presented and their detection performances compared.

In addition, soft combining rules such as maximal ratio combining, equal gain combining and linear weighted combining of individual CR user performance results are also explored. The authors present an optimum number of users that can be used in hard combining rules.

In [56] [59], a generalized likelihood ratio test (GLRT) application is proposed on a cyclostationary feature CSS to enable detection of cyclostationary signals using multiple cyclic frequencies. Each co-operating user conveys local sensing results to the fusion centre using a censoring technique. Results for this work shows improved energy efficiency, despite the added complexity of this approach. However, it is noteworthy that research effort presented in this work has been over AWGN channel.

2.3 Project Tools

The literature review also presents the set of tools that would be used in the design and implementation of the project. All the components of the project are designed, constructed and implemented in a MATLAB software environment. The following sub section is an introduction to MATLAB software and briefly explains its functions relevant to this project.

2.3.1 Introduction To MATLAB Software

MATLAB is a high performance language for technical computing and integrates computation, visualisation and programming [60]. MATLAB incorporates sophisticated data structures, contains built-in editing and debugging tools, and supports object-oriented programming.

MATLAB offers both command line and graphical user interface, which can be used to design, build and simulate complex engineering models and investigate their behaviour. With excellent telecommunications and digital signal processing toolboxes, MATLAB has functions that can perform modulation and demodulation functions, channel coding functions and emulate various channel models for a wireless environment.

In addition, MATLAB is very useful in cognitive radio research as it incorporates functions that can emulate conventional spectrum sensing techniques and therefore allow for the simulation of their performance.

The computation functions allow MATLAB to build arrays that can calculate Cognitive Radio performance metrics such as probability of detection, miss and false alarm.

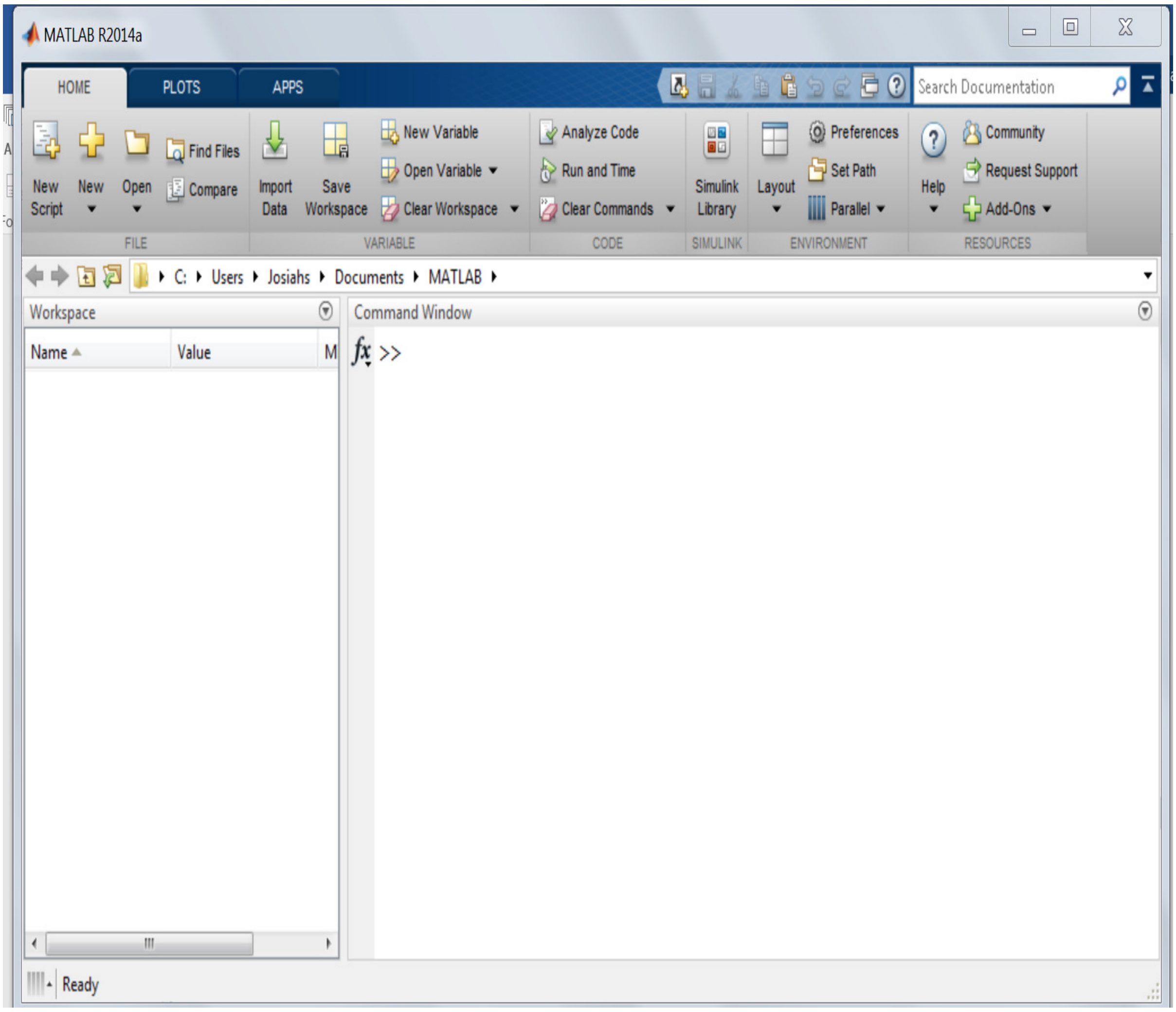

Figure 2-11*:* A screenshot of the MATLAB software interface.

2.4 Chapter Summary

This chapter presented in detail, a review of the fundamental concepts of spectrum sensing in cognitive radio. A discussion of transmitter-based spectrum-sensing techniques in the form of energy detection, cyclostationary feature detection and matched filter detection was made. Co-operative spectrum sensing technique concepts were also introduced. The chapter also presented mathematical and statistical derivations that support the methodologies used in the design and implementation of experiments for the analysis of spectrum sensing techniques performance.

The chapter also highlighted related research effort available in literature for all spectrum sensing techniques studied in this dissertation work, in particular the work so far carried out to enhance the performance of conventional spectrum sensing techniques.

More importantly, the chapter also highlighted some research gaps that still need to be addressed in the analysis of spectrum sensing techniques in the practical cognitive radio-operating environment, thus providing the basis for this dissertation work.

CHAPTER THREE

3 METHODOLOGY

This chapter presents the methodology for developing a simulation test-bed for evaluating spectrum sensing techniques for cognitive radio applications, and the methods of performance evaluation to be used in investigating the effectiveness of these techniques under the Rayleigh fading channel model conditions. The steps involved in this project are outlined, showing how it progressed from the initial conception and problem definition stage, through design and implementation to final testing and the conclusions and recommendations.

The methodology used in this project is, at a high level, following the structure of the Waterfall Model [61], with feedback loops showing maintenance activities and phases repeated. At a lower level, the methodology applies the spiral model approach, with a series of iterative cycles to ensure stepwise refinement and incremental improvement throughout the development of the project [62].

As shown in Figure 3-1, the project was completed in seven main steps

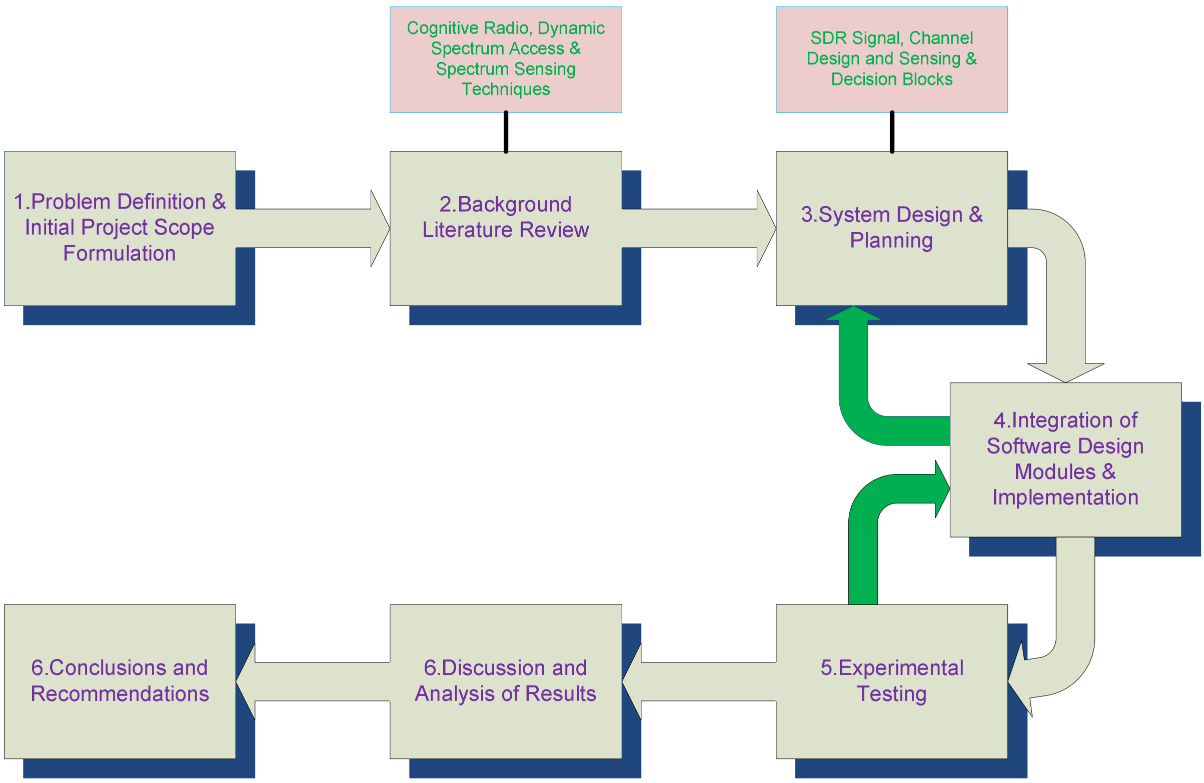

Figure 3-1: Overview of the spectrum sensing techniques performance evaluation project methodology.

The following sections describe in detail the steps outlined in the project methodology overview diagram above.

3.1 Problem Definition and Initial Project Scope Formulation

The first step in this project was to envision, identify and define the problems that today and future wireless devices face due to spectrum scarcity. Cognitive radio technology is widely seen as the most promising solution in overcoming the problems associated with spectrum overcrowding and inefficient utilization. Consequently, considerable research effort is underway in the field of cognitive radio and dynamic spectrum access.

In particular, spectrum sensing, which identifies the status of spectrum occupation by a transmitter has stimulated considerable interest in academia. However, the bulk of research work available in literature has not considered the influence of the physical environment in studying the performance of spectrum sensing algorithms.

In line with the problem definition outlined in Chapter One, we developed the main objective and derived sub-objectives within the formulated scope that we envisaged would sufficiently address the problem statement. These formed the core foundation on which reference was made throughout the design, implementation and testing of the system.

3.2 Background and Literature Review

The second stage of the project was to prepare the background and literature review. In Chapter 2, cognitive spectrum sensing techniques were introduced. These include energy detection, cyclostationary feature detection, matched filter and energy detection based co-operative spectrum sensing. During this stage, the main focus was to develop a firm understanding of cognitive radio in the context of spectrum sensing techniques, and enabling technologies. This was to facilitate a logical, sequential and orderly development of the building blocks, which the project would consist of.

Building on principles already discussed in the literature review, this section of the methodology provides more details on derivations of the mathematical models and performance metrics used in the development of MATLAB code in the design phase. Although abstracted in MATLAB functions, these models are a key aspect in the development of the MATLAB code.

The major aim of this project is to evaluate the performance of spectrum sensing techniques. Therefore, it is important to understand the performance metrics involved. These are based on parameters derived from the field of statistical signal theory. In particular, detection theory and hypothesis testing parameters namely probability of detection, false alarm and misdetection are used in analysing the performance of spectrum sensing techniques. Subsequent sub-sections provide definitions of these statistical parameters and the tools used in performance measurements in the form of receiver operating characteristic (ROC) curves. A general system model is presented, followed by a discussion of the block diagrams that build up each spectrum sensing technique. This is useful in understanding how each technique is decomposed into modules for implementation during design.

3.2.1 System Model

As already highlighted in Chapter Two, analytically, determining the presence or absence of the primary signal ***x(t)*** for all the spectrum sensing techniques is reduced to an identification problem. Depending on the idle state or busy state of the primary user, in the presence of noise the signal detection at the secondary user can be modelled as a binary hypothesis testing problem [22], given as

Hypothesis 0 , $\boldsymbol{H_0}$ SIGNAL IS ABSENT

Hypothesis 1, $\boldsymbol{H_1}$ SIGNAL IS PRESENT

This can be represented as follows:

$$x(t) = \begin{cases} n(t) & H_0 \\ h * s(t) + n(t) & H_1 \end{cases} \qquad (3.1)$$

where,

$x(t)$ is the signal sample to be analysed at time t

$n(t)$ is the additive noise assumed to be white Gaussian with zero mean and the variance σ^2

h is the complex channel gain (for this dissertation, Rayleigh channel) between the transmitted signal and secondary user.

$s(t)$ is the transmitted signal from the primary user.

Based on the model outlined above, the goal is to observe the received signal *x(t)* at a given time t, then construct some rule to decide the correct hypothesis depending on a test statistic either being greater or smaller than a pre-determined threshold value κ.

To evaluate the performance of such a decision rule, we use statistical performance metrics derived from the detection theory.

Although the system model expression for the hypothesis test given in equation 3.1 is representative of all the spectrum sensing techniques studied in this dissertation, it is important to note that the test statistic derivation depends on the particular spectrum sensing technique under consideration.

3.2.1.1 Spectrum sensing performance metrics

This sub-section discusses the sensing quality parameters, which constitute the performance metrics used in evaluating the accuracy of the aforementioned techniques. These are listed below:

- The Probability of Detection P_D
- The Probability of False Alarm P_{FA}
- The Probability of Miss P_M

In this context, the probability of detection specifies the probability that the spectrum sensing detector makes a correct decision regarding the presence of primary user transmission (H_1). As such, the probability of detection is an indication as to the level of interference protection provided to primary user by the sensing technique employed in the secondary user. A robust spectrum sensing technique gives a higher P_D, and provides more interference protection to the primary user.

A false alarm occurs when the sensing technique assumes H_1 when in fact the correct decision is H_0. In detection theory, this is specified as a false alarm and the associated probability is denoted by P_{FA}. When a false alarm occurs, the CR will not transmit its data, thus missing an opportunity to utilize the available spectrum. A high probability of false alarm implies a higher likelihood of missed opportunities that render a spectrum sensing technique inefficient. P_{FA} is a very important design parameter in cognitive radio and should be kept reasonably low.

A misdetection occurs when the sensing algorithm assumes H_0 when the correct decision is H_1.

Under these circumstances, the SU will initiate transmission while spectrum is occupied by the PU, resulting in interference. This is in contravention of the concept of opportunistic spectrum access and should be avoided at all times.

3.2.1.2 Sensing techniques performance measurement tools

In the analysis of spectrum sensing techniques, the Receiver Operating Characteristics (ROC) curves usually qualify performance of the receiver (CR). By definition, ROC curves are a way of graphically displaying the diagnostic performance of a given test [63]. The ROC curve plots the sensitivity of a test over the entire range of possible specificities. In the context of spectrum sensing, ROC curves are applied to highlight trade-offs between probability of detection and probability of false alarms to determine the value of an optimal threshold. In statistics, the probability of detection is complimentary to the probability of misdetection. It follows that complementary ROC curves (that is $P_M = 1 - P_D$ vs P_{FA}) can also be used in depicting the performance of a receiver.

As already highlighted, apart from quantifying the performance of a receiver, ROC curves are an important design tool as they allow researchers to explore the relationship between P_D and P_{FA}. Fixing one parameter whilst varying the other in plotting ROC curves enables researchers to study various scenarios of interest.

In addition to the ROC curves, to illustrate the influence of the environment to the performance of spectrum sensing techniques studied in this work, probability of detection vs SNR plots are also used for performance analysis.

To determine the presence or absence of the primary signal in spectrum sensing, a test statistic, whose value is compared to a threshold value is used. The derivation of the test statistic depends on the model of the spectrum sensing technique. The following section presents the mathematical derivations of the test statistics for ED, CFD, MFD and ED based co-operative techniques.

3.2.2 Spectrum Sensing Test Statistic Mathematical Derivations

3.2.2.1 Energy Detection

The transmission status of the primary user is determined by comparing the output of the energy detector to a threshold value. Figure 3-2 overleaf illustrates the sequence of the signal processing blocks leading to this comparison.

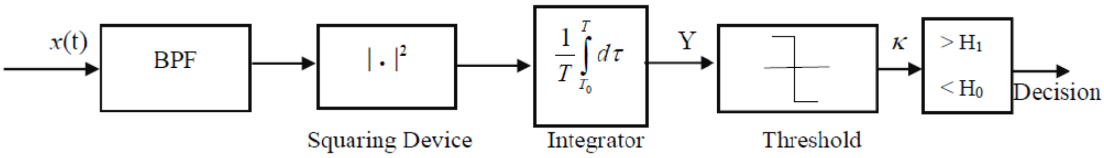

Figure 3-2*:* Block Diagram of energy detection method [64]

In implementing the energy detector, the received signal ***x(t)*** is first filtered by a BPF and then passed to a squaring device. Band-limiting the signal helps in reducing the noise bandwidth so that the input to the squaring device has a flat noise spectral density. The output of the squaring device is then integrated over the time interval T to get the decision statistic Y which is essentially the energy of the received signal. The decision statistic is then compared to the threshold value κ and a decision is made as to whether the received signal contains primary transmission or not. A decision on spectrum occupancy is made by comparing the decision statistic and the threshold value.

Derivation of P_D ***and*** P_{FA}

Referring back to equation (*3.1)*, the sample of *n(t)* are assumed to be zero-mean Gaussian random variables with variance N_0W with N_0 and W denoting the single-sided noise power spectral density and single-sided signal bandwidth respectively [65].

The output of the integrated signal over the time interval T is given as :

$$Y = \frac{1}{T}\int_{0}^{T} |x(t)|^2\, dt \qquad (3.2)$$

The output of the integrator, which is a measure of the energy of the received signal over the interval T, constitutes the test statistic whose comparison with the threshold value determines whether the primary signal is present or not.

Denoting the observation time bandwidth as $u = TW$, the test statistic follows the central chi-square distribution with $2u$ degrees of freedom under the H_0 hypothesis and the non-central chi-square distribution with $2u$ degrees under the H_1 hypothesis [66] [65].

The corresponding distribution function of the test statistic in the presence of AWGN noise is expressed as:

$$P_Y(Y) = \begin{cases} \frac{1}{2^u \Gamma(u)} Y^{u-1} e^{-\frac{Y}{2}} & : H_0 \\ \frac{1}{2}\left(\frac{Y}{2\gamma}\right)^{\frac{u-1}{2}} e^{-\frac{(Y+2\gamma)}{2}} I_{u-1}\left(\sqrt{2Y\gamma}\right) & : H_1 \end{cases} \quad (3.3)$$

where $\gamma \triangleq |h|^2 E_s/N_0$ is the corresponding instantaneous signal to noise ratio (SNR), E_s is the signal energy, $\Gamma(.)$,$I_n(.)$ denote the gamma function and the modified Bessel function of the first kind [65].

Introducing the detection threshold κ and incorporating the performance metrics discussed earlier, that is probability of detection, probability of false alarm and probability of miss.

$$P_{FA} = \Pr(Y > \kappa) \mid H_0 \quad (3.4)$$

$$P_D = \Pr(Y > \kappa) \mid H_1 \quad (3.5)$$

$$P_M = 1 - P_D \quad (3.6)$$

The probability of detection and probability of false alarm are deduced by integrating (3.3) over the interval between the threshold and infinity$\{\kappa, \infty\}$, which yields

$$P_{FA} = \frac{\Gamma(u, \frac{\kappa}{2})}{\Gamma(u)} \quad (3.7)$$

$$P_D = Q_u\left(\sqrt{2\gamma}, \sqrt{\kappa}\right) \quad (3.8)$$

Where $Q_m(a,b)$ and $\Gamma(.,.)$ denote the generalised **u***th* order Marcum Q function and the upper incomplete gamma function respectively.

The above mathematical expressions form the basis of MATLAB code implementation for the evaluation of energy detection spectrum sensing performance.

3.2.2.2 Cyclostationary Feature Detection

As highlighted in the previous chapter, cyclostationary feature detection exploits cyclostationary characteristics exhibited by many transmitted radio signals based on their modulation type, data rate and carrier frequency. The block diagram shown in Figure 3-3 shows the signal processing blocks that leads to the extraction of the cyclostationary feature.

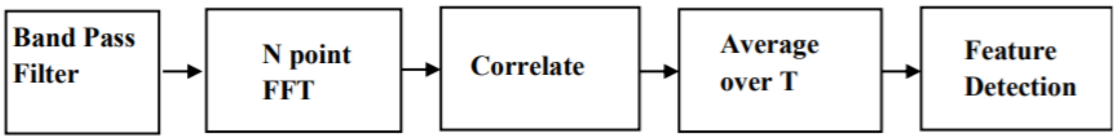

Figure 3-3: Cyclostationary Feature Detection Block Diagram

Cyclostationary Feature Detection Theory

The theory of cyclostationary feature detection is anchored on the model given in (3.1).

Assuming a complex sine wave signal s(t) defined as:

$$s(t) = Ae^{j(2\pi f_0 t+\theta)} \tag{3.9}$$

where **A** represents the magnitude of the signal and $A \neq 0$, f_0 is the signal frequency and θ represents the phase.

After addition of AWGN to the signal, it can be represented as

$$x(t) = Ae^{j(2\pi f_0 t+\theta)} + n(t) \quad (3.10)$$

First, a factor $e^{-j2\pi\alpha t}$, related to the cyclic frequency α is added to the received signal ***x(t)***, before calculating its average on a certain cyclic frequency [38].

The factor addition yields

$$y(\alpha, t) = x(t) * e^{-j2\pi\alpha t} \qquad (3.11)$$

Calculating the average of $y(\alpha, t)$ assuming detection time length of t_0 and defining a variable $M(\alpha, t_0)$ for a certain cyclic frequency α as follows

$$M(\alpha, t_0) = \frac{1}{t_0}\left|\int_0^{t_0} y(\alpha, t)dt\right| = \frac{1}{t_0}\left|\int_0^{t_0} x(t) * e^{-j2\pi\alpha t}dt\right| \qquad (3.12)$$

Assuming the received signal is in complex form without noise as given by equation (3.9), then the result of detection in cognitive radio is given by:

$$M(\alpha, t) = \begin{cases} \dfrac{\left|\int_0^{t_0} s(t) \times e^{-j2\pi\alpha t}dt\right|}{t_0} = \dfrac{\left|\int_0^{t_0} Ae^{j(2\pi f_0 t+\theta)} \times e^{-j2\pi\alpha t}dt\right|}{t_0} \\ \dfrac{\left|Ae^{j\theta}\right|}{t_0}\left|\displaystyle\int_0^{t_0} e^{j2\pi(f_0-\alpha)t}dt\right| = \dfrac{\left|Ae^{j\theta}\right|}{t_0}\left|\delta(f_0-\alpha)\right| \end{cases} \qquad (3.13)$$

However, as most electromagnetic signals are transmitted in real form, we can re-write (3.13) in simplified form by ignoring noise as given below

$$M(\alpha,t) = \begin{cases} \frac{1}{t_0}|\int_0^{t_0} y(\alpha,t)dt| = \frac{1}{t_0}|\int_0^{t_0} x(t) \times e^{-j2\pi\alpha t}dt| \\ \frac{1}{t_0}|\int_0^{t_0} Acos(2\pi f_0 t + \varphi) \times e^{-j2\pi\alpha t}dt| \\ \frac{|A|}{2t_0}|e^{-j\varphi}\Psi_1(f_0,\alpha) + e^{j\varphi}\Psi_2(f_0,\alpha)| \end{cases} \tag{3.14}$$

where $\Psi_1(f_0,\alpha)$ and $\Psi_2(f_0,\alpha)$ are functions related to frequency f_0 and cyclic frequency α given as follows:

$$\Psi_1(f_0,\alpha) = \int_0^{t_0} e^{-2\pi(f_0+\alpha)t}dt \tag{3.15}$$

$$\Psi_2(f_0,\alpha) = \int_0^{t_0} e^{-2\pi(f_0-\alpha)t}dt \tag{3.16}$$

A MATLAB function observes the peak of function (3.14), to determine the availability status of the primary signal.

3.2.2.3 Matched Filter Detection

The MFD is a linear filter designed to maximize the output signal ratio for a given input signal [67]. As highlighted in literature review, the secondary user must have a priori knowledge of the primary user. Figure 3-4 illustrates the application of the statistical binary hypothesis model to the output of MFD in determining the presence or absence of the primary signal.

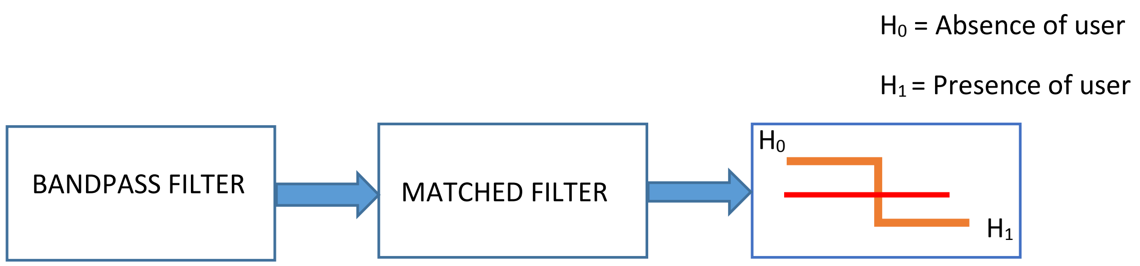

Figure 3-4: Block Diagram of matched filter detection method

The probability of detection and false alarm are calculated using the expressions below.

$$P_{d,M} = Q\left(\frac{\xi - E}{\sigma_w \sqrt{E}}\right) \qquad (3.16)$$

$$P_{f,M} = Q\left(\frac{\xi}{\sigma_w \sqrt{E}}\right) \qquad (3.17)$$

where $Q(.)$ is the Gaussian complexity distribution function, E is the energy of the deterministic signal of interest and σ_w^2 is the noise variance. The software matched filter detection function that implements MFD performance evaluation is based on the above equations.

3.2.2.4 Energy Detection Based Co-operative Spectrum Sensing

Energy detection based co-operative spectrum sensing technique is essentially a group of spatially separated energy detectors that co-operate in determining the status of spectrum occupancy. After each energy detector makes a decision regarding the availability of a spectrum hole, it sends the decision to the fusion centre which performs decision fusion and makes a combined decision.

This project used a total of 7 energy detectors with a fusion centre that employed majority decision rule as shown in Figure 3-6.

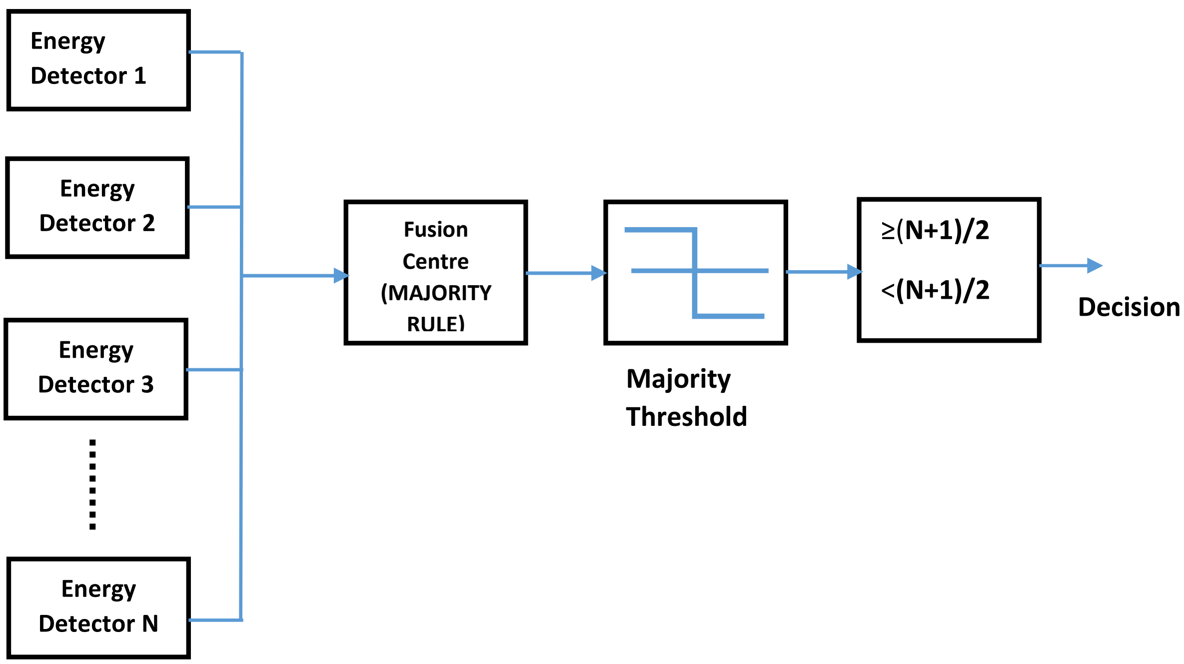

Figure 3-5: Energy detection based co-operative sensing employing MAJORITY decision fusion rule.

The fusion centre will decide that spectrum is available if more than 7 energy detectors detect a spectrum hole, and decide otherwise if 7 or less energy detectors detect a spectrum hole.

3.3 System Design & Planning

The third stage in the development of the project was the planning and system design stage. This two-stage process involved first, an assessment of the project requirements to determine the set of tools that would be required and then breaking the project into smaller, manageable modules. This would simplify the development of software components for the project.

The design overview and components for the spectrum sensing performance evaluation project is shown in Figure 3-6. The design would consist of the SDR signal generator, convolution encoder, transmitter, Rayleigh fading channel, spectrum sensing algorithm and spectrum sensing decision.

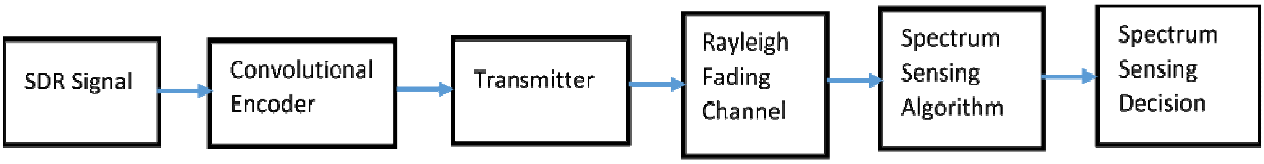

Figure 3-5: MATLAB software design block diagram

An alternative approach would have used RTL-SDR device and GNU Radio flowgraphs to generate the primary user signal as shown in Figure 3.7. This could however, not be implemented, as the MATLAB version used had no function to integrate with an external signal source.

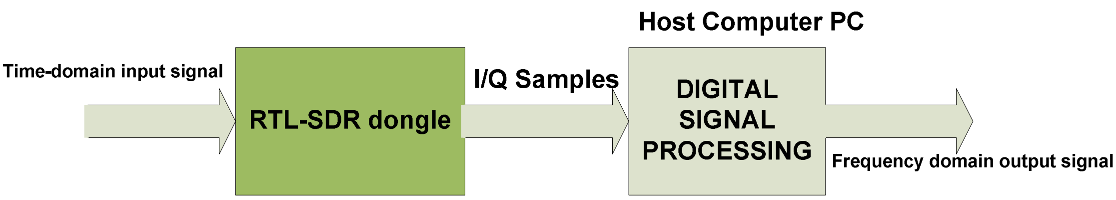

Figure 3-6: Primary signal generation by RTL-SDR device

The SDR signal generation is the first process that initiates spectrum sensing for all the spectrum-sensing techniques. The SDR signal is then fed into a convolution encoder.

The convolution encoder adds some redundancy to the digital signal, to make it robust to the harsh channel conditions in the transmission channel. The transmitter sends the signal into the wireless environment so that a CR equipped receiver in the vicinity is able to sense the environment to decide if there is a PU transmission or not.

The Rayleigh fading channel block simulates the Rayleigh fading channel conditions through which a primary user transmission traverses before a CR receives the distorted signal. This is the software implementation of the spectrum sensing technique in MATLAB. In this case, it consists of energy detector, cyclostationary feature detection, matched filter detection and energy detection based co-operative spectrum sensing techniques.

This is the final block that decides whether a primary signal transmission is present or not. It is the core of the spectrum sensing technique performance, as its accuracy directly measures the performance of spectrum sensing technique.

3.4 Integration of Software Design Modules and Implementation

The fourth stage in the development of the spectrum sensing techniques performance evaluation is the implementation and integration phase. In this stage, the design block functions formulated in the design stage are implemented in MATLAB software. Each block executes a specific discrete function, but cannot operate in isolation. So, in addition to the software implementation of the design blocks, this stage integrates the design blocks into a single, complete unit that can simulate the performance of the spectrum sensing techniques considered in this study.

3.5 Experimental Testing

After the implementation and integration stage, a complete system to evaluate the performance of each spectrum sensing technique is now available. Each technique was simulated in MATLAB and ROC curves plotted to illustrate the relationship between probability of detection and probability of false alarm for each spectrum sensing technique.

In addition, charts showing the relationship between probability of detection and signal to noise ratio were also produced.

3.6 Discussion and Analysis of results

This stage gives a comprehensive discussion and analysis of simulation results obtained during experimental testing. Simulation results for energy detection, cyclostationary feature detection, matched filter detection and energy detection based co-operative spectrum sensing through a Rayleigh fading channel are discussed and analysed. Comparisons are drawn on these performances, with a discussion on how the energy detection co-operative spectrum sensing technique improves the performance.

3.7 Conclusions and Recommendations

The final stage presents the conclusions drawn from the project and the effectiveness of the project workflow. This involves assessing and measuring the extent to which the main objective and sub-objectives were met. The stage also discusses observations and lessons noted during the project execution. Finally, the phase presents recommendations for future work that would improve research on the performance of spectrum sensing techniques in a Rayleigh fading channel environment.

3.8 Chapter Summary

This chapter presented the structure of the methodology used in achieving the objectives and sub-objectives set in this project. The chapter introduced the waterfall model used for high-level project planning, and identified the main stages involved and how they are interlinked. A revisit of the spectrum sensing techniques was made to clearly understand how the mathematical derivations apply to the system design. In addition, the chapter also discussed the performance metrics that are key to the evaluation of spectrum sensing techniques performance considered in the project. Furthermore, the chapter briefly discussed the system design and integration, experimental test-bed setup, testing, and analysis of results.

Finally, the chapter gave a brief account of the conclusions and recommendations as the final stage of the project methodology.

CHAPTER FOUR

4 DESIGN AND IMPLEMENTATION

This chapter presents the design flow of the spectrum sensing techniques performance evaluation project. It outlines in detail the logical flow and formulation of the modules that form the discrete components used in the performance evaluation framework for each spectrum sensing technique. The design flow lays the foundation on which software code for the evaluation of spectrum sensing performance is developed.

The flowchart in Figure 4-1 below depicts the general process flow for the project design.

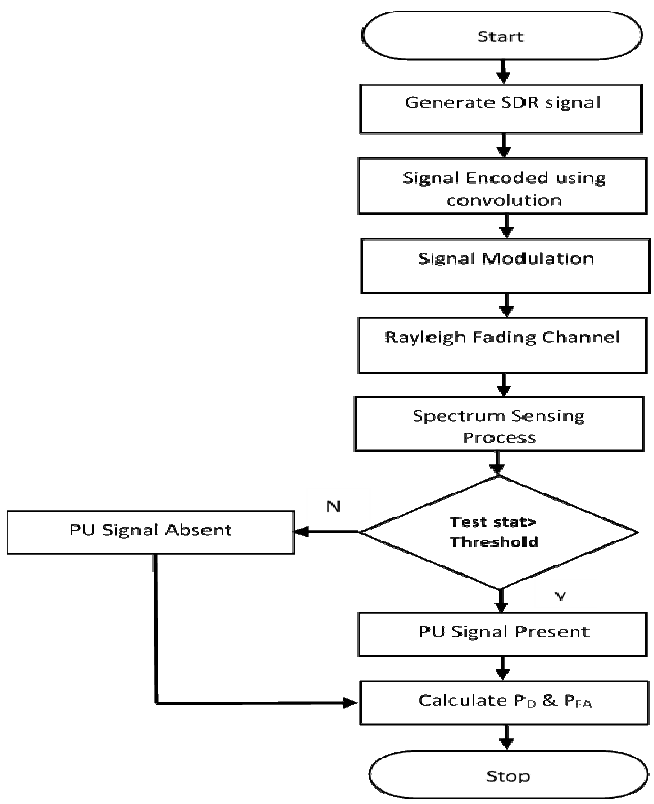

Figure 4-1: General Design Flowchart for the Spectrum Sensing Performance Evaluation Project

4.1 SDR Signal Generation

The first stage in the design process of this project involves generating a signal in MATLAB. A total of 5 frames of length 200 bits is generated, with each message signal represented by 8 bits. A series of digital messages consisting of 1s and 0s is then randomly generated and fed into a convolutional process for encoding. The code snippet below shows the implementation of the SDR signal in MATLAB.

```
%% generate SDR based signal

M=2; % modulation

no_of_frame=5; % no of frames to transmitt

frmlen=200; % frame length

sym_len=256; % symbol length

blkm=log2(M);lenm=frmlen*no_of_frame;

% randomly generate message

mess_data=randsrc(1,lenm,0:1);
```

4.2 Convolutional Encoder

Following the design of the SDR signal with a series of discrete messages, the message blocks denoted as *mess_data* are fed into a convolutional encoder. The role of the convolutional encoder is to introduce some redundancy bit to the SDR signal so that it can be recovered after traversing the hostile Rayleigh fading channel. The implementation used in this project applies a ½ rate convolutional encoder, so it adds an extra redundant bit for every single message bit. The code snippet below shows the implementation of the convolutional encoder parameters in MATLAB.

```
function dataout=CONVOLUTIONAL_ENCODER_puncture(data_in,rate);

[r c]=size(data_in);

code_rate=[1/3 1/2 2/3 3/4];

punct_matrix={[1 1 0 1],[1 1],[1 0  1 1],[1 0 1 1 1 0]};

[r_code c_code]=find(code_rate==rate);

mat=punct_matrix{1,c_code(1)};
```

```
msg=data_in;

t = poly2trellis(7, [171 133]); % Define trellis.

punctcode= convenc(msg, t, mat); % Length is (2*len)*rate

dataout=punctcode;
```

The mess_data is then fed into the convolution encode process as shown below.

```
rate=1/2;% apply convolutional encode process

conv_out=CONVOLUTIONAL_ENCODER_puncture(mess_data,rate);

len=length(conv_out);
```

4.3 Signal Modulation

After convolution encoding, modulation is applied to the signal. In this project, the signal is modulated using Quadrature Phase Shift Keying (QPSK). The modulation process function is implemented in MATLAB as shown in below code snippet.

```
function mod_signal=modulation_process(psk_mod_obj,data_in);

mod_signal=modulate(psk_mod_obj,data_in);
```

The output to the convolution encoder *data_de1* is fed into the modulation process as shown below and the output is the final modulated signal denoted by*mod_signal1*

```
qpsk_mod_obj=modem_object_create(M);

mod_signal1=modulation_process(qpsk_mod_obj,data_de1);

final_mod_data=mod_signal1;
```

4.4 Rayleigh Fading Channel

This project simulates the performance of spectrum sensing techniques through a Rayleigh fading channel. In order to achieve this, a Rayleigh channel model with fading characteristics is designed in MATLAB. It incorporates real world parameters such as path delay and path gain ranges. In addition the Rayleigh channel model in this project defines the signal to nose ratio of between -30dB to 30dB. The code snippet below illustrates the Rayleigh fading channel implementation in MATLAB.

```
% create rayleigh channel
pathdly=[0 1e-5 2.5e-5 6e-5];                  % Path delays
pathgain=[0 -1 -10 -1];                         % Avg path power gains
chan=rayleighchan(1e-3,0, pathdly, pathgain);
    indx=1;
% snr value
snr_range=-30:2:30;
```

4.5 Spectrum Sensing Techniques

After the generation and transmission of the SDR signal through a Rayleigh fading channel, this project designs the spectrum sensing techniques in MATLAB. The implementation for each technique is different and the design is therefore discussed separately in the following subsections.

4.5.1 Energy Detection

The energy detection algorithm evaluates the cumulative energy level of the wireless signal over a time period and compares this test statistic to the threshold value to determine if there is PU transmission or not.

The design flow for the energy detection spectrum sensing technique is shown in Figure 4-2.

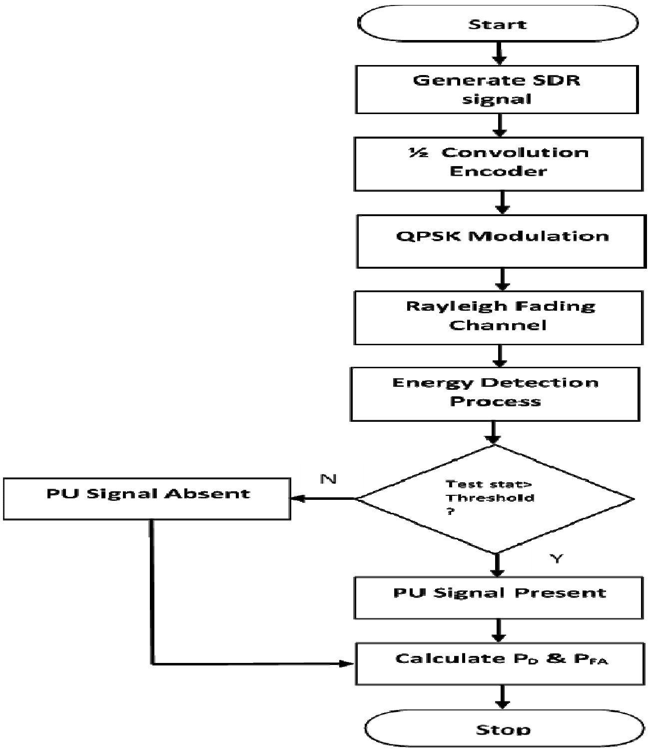

Figure 4-2: Design Flow Diagram for Energy Detection Spectrum Sensing.

The design considers and adds the effects of AWGN noise to the signal propagation. Below is a MATLAB code snippet implementation for energy detection.

```
indx=1;

% snr value

snr_range=-30:2:30;

propval=0.1;% pf val

for snr_ind=snr_range

   rxed_data_in=reshape(final_txed_datas,[(sym_len) length(tx_data)/lemb]);

   % adding noise

   for km=1:length(tx_data)/lemb

      rx_data_in2=rxed_data_in(:,km);

      rx_data_in2=filter(chan,rx_data_in2);
```

```
    rx_data_in2=awgn(rx_data_in2,snr_ind);
    % energy detection applying
    cvalm=(rx_data_in2(:));
    prop_fals=propval;threshold_value=qfuncinv(prop_fals);
    ddata1=(abs(cvalm).^2)>threshold_value;
    cntval=length(find(ddata1));
    pdval(km)=cntval/length(ddata1);
end
```

4.5.2 Cyclostationary Feature Detection

The design flow for performance evaluation of the cyclostationary feature detection is as shown in Figure 4-3.

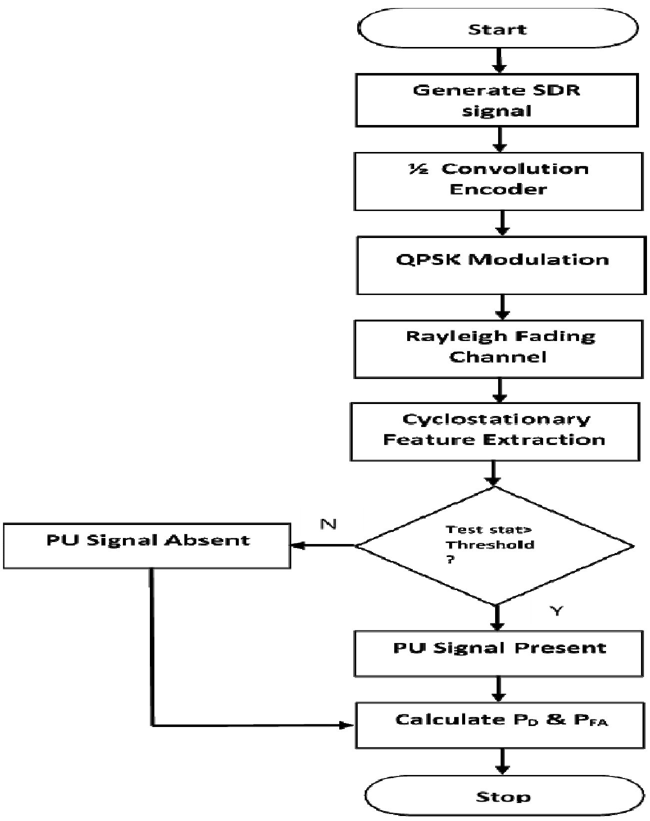

Figure 4-3: Design Flow Diagram for Cyclostationary Feature Detection Spectrum Sensing.

The cyclostationary feature extraction process computes the cyclostationary feature in equation (3.14) and incorporates the effects of noise and channel distortions. Below is the MATLAB code implementation of the CFD function.

```
function Coh =cyclo_stat_detect(in_signal,k)

L=length(in_signal);                % signal length

alpha=k/L;

filter_win_len=256;                         % window length

overlap_block=fix(2/3*filter_win_len);  % block overlap

nfft = 2*filter_win_len;            % FFT length

in_signal1=in_signal;

if length(filter_win_len) == 1

   filter_win_len = hanning(filter_win_len);

end

filter_win_len = filter_win_len(:);

n = length(in_signal);

nwind = length(filter_win_len);

in_signal1 = in_signal1(:);

in_signal = in_signal(:);

t = (0:n-1)';

in_signal1 = in_signal1.*exp(-1i*pi*alpha*t);

in_signal = in_signal.*exp(1i*pi*alpha*t);

Syx=cyclic_spec_process(in_signal1,in_signal,0,nfft,overlap_block,filter_win_len);

Sy=cyclic_spec_process(in_signal1,in_signal1,0,nfft,overlap_block,filter_win_len);

Sx=cyclic_spec_process(in_signal,in_signal,0,nfft,overlap_block,filter_win_len);

Coh.K = Sx.K;

Coh.f = Sx.f;
```

```
Coh.Syx = Syx.S;

Coh.Sy = Sy.S;

Coh.Sx = Sx.S;

Coh.C = Syx.S./sqrt(Sy.S.*Sx.S);
```

4.5.3 Matched Filter Detection

The MFD is a linear filter designed to maximize the output signal ratio for a given input signal. In this project the MFD process compares the signal input to a priori known signal waveform and determines the absence or presence of the primary signal depending on the comparison. Figure 4-4 below shows the design flow of the MFD performance evaluation.

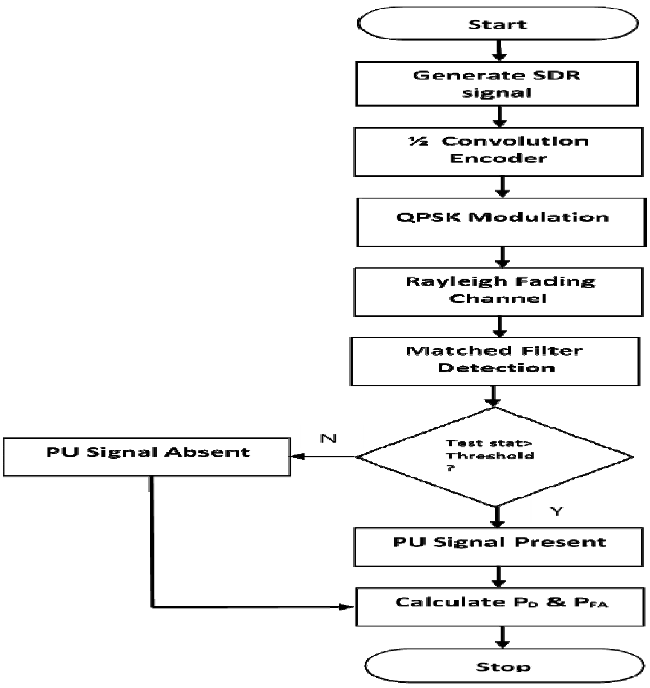

Figure 4-4: Design Flow Diagram for Matched Filter Detection Spectrum Sensing.

The matched filter detection process implementation is as shown in the below MATLAB code snippet.

```
%% create matched filter

match_filt=phased.MatchedFilter('SpectrumWindow','Taylor');

% matched filter applying
    rx_data_in2=step(match_filt,rx_data_in2);
    cvalm=(rx_data_in2(:));
    prop_fals=propval;
    threshold_value=qfuncinv(prop_fals);
    ddata1=(abs(cvalm).^2)>threshold_value;
    cntval=length(find(ddata1));
    pdval(km)=cntval/length(ddata1);

  end
 finalpdval(indx)=1-mean(pdval);
 finalsnrval(indx)=snr_ind;
 indx=indx+1;
end
```

4.5.4 Co-operative Spectrum Sensing

Based on the majority rule fusion centre, this project investigates the performance of energy detection co-operative spectrum sensing. The design flow for the development of MATLAB code to implement the performance evaluation is shown in Figure 4-5 overleaf.

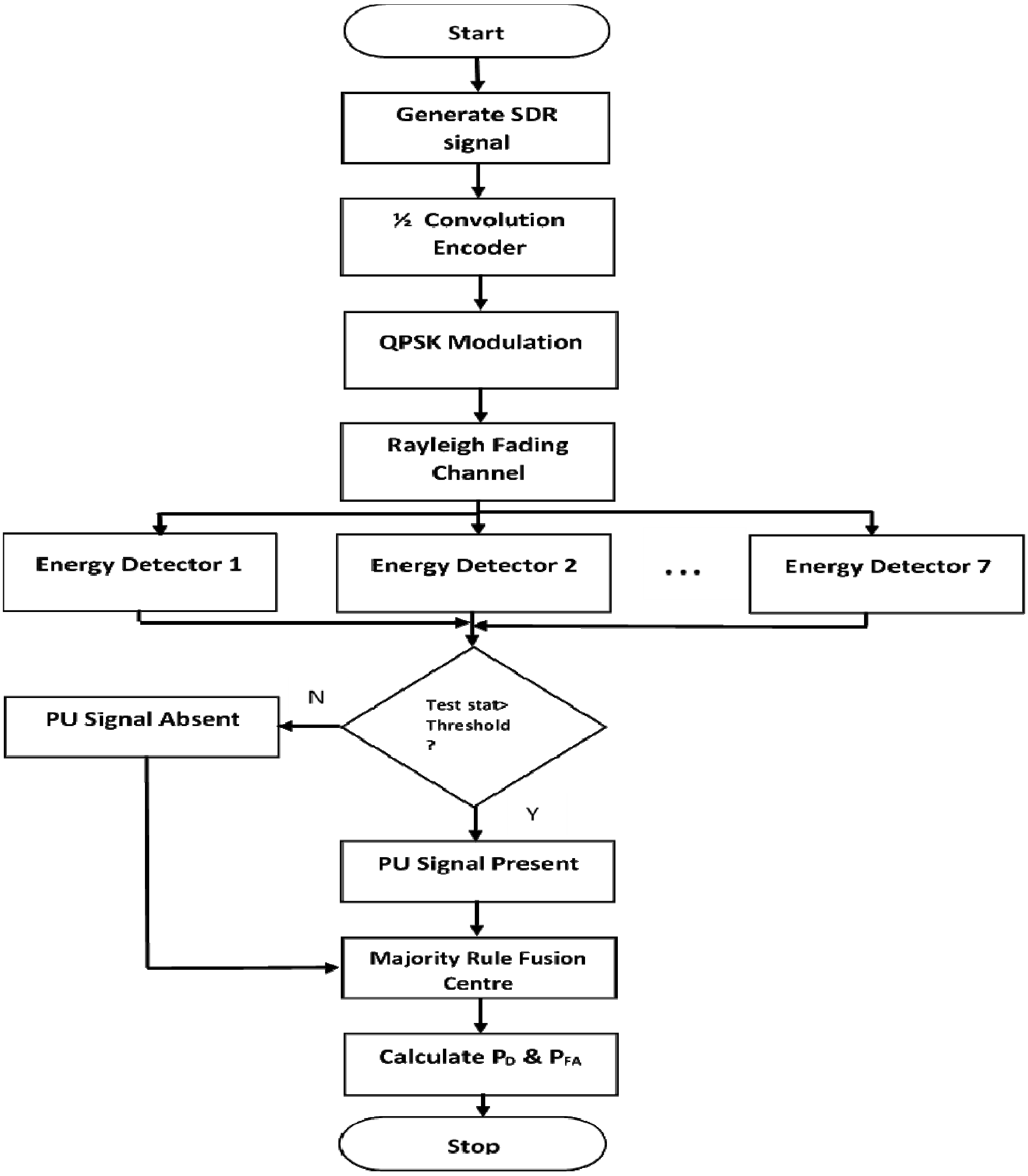

Figure 4-5: Design Flow Diagram for Energy Detection Co-operative Spectrum Sensing

In this dissertation a total of 7 energy detectors, which mimic spatially located SUs are used. After sensing the wireless environment they relay their sensing results to the majority fusion centre which determines the presence or absence of spectrum, before the P_D and P_{FA} is calculated under varying SNR conditions.

4.6 Chapter Summary

This chapter began by presenting the general flow of the design approach used in the project and illustrated, by way of flowcharts on how the different components of the project are logically linked and integrated into a complete system.

The major components described are the SDR generation, convolution encoder, modulation process, Rayleigh fading channel and the spectrum-sensing process. In addition, the characteristic parameters for each of the project components is also described. The chapter then described the separate design flow for all the spectrum sensing techniques which are part of this project and showed snippets of the project implementation in MATLAB code.

CHAPTER FIVE

5 Discussion and Analysis of Results

The previous chapter presented in detail, the design and implementation flow for the performance evaluation of the spectrum sensing techniques investigated in this study. The development strategy proceeded from a high-level abstract design in the form of flowcharts, to the MATLAB low-level code that implemented the simulation of these sensing techniques with Rayleigh fading channels, and from which performance evaluations were completed. This chapter presents results for these simulated sensing techniques and performs a comparative analysis of the performance results. Simulated results are presented in the form of plots of the probability of detection under varying levels of signal-to-noise ratios, as well as ROC and complementary ROC curves for the spectrum sensing techniques under discussion.

5.1 Simulation Results

This section presents the results of the simulations as set out according to the designs in chapter 4. In particular ,the set of simulation results discussed are as outlined below.

- Probability of detection performance simulation for Energy Detection.
- Receiver Operating Characteristics (ROC) curve for Energy Detection technique.
- Probability of detection performance simulation for Cyclostationary Feature detection.
- Probability of detection performance simulation for Matched Filter Detection.
- Probability of detection performance simulation for Energy detection based cooperative spectrum sensing technique.
- Complementary ROC curve for energy detection based cooperative spectrum sensing.

The MATLAB simulation results for the stated scenarios are presented and discussed in the following subsections in the same order as they are listed above.

5.1.1 Energy Detection Results

The performance of an energy detection algorithm operating through a Rayleigh fading channel is simulated in this section and the results for probability of detection vs SNR are depicted in Figure 5-1. In this simulation, the probability of false alarm $\mathbf{P_{FA}}$ is set to 0.1. Consistent with results obtained in other works such as [12] and [35], it can be deduced that the performance is poor at low SNR values and greatly improves at higher SNR values.

At -10dB, the probability of detection is approximately 0.1 but increases sharply to more than 0.8 at SNR values greater than 0dB. As outlined earlier in the main objectives of this study, emphasis has been placed on environmental characterisation. Thus, we incorporate fading channel parameters to the simulation environment, unlike the aforementioned studies. This provides a more accurate test-bed in researcher's attempt to investigate channel influence to the performance of spectrum sensing techniques.

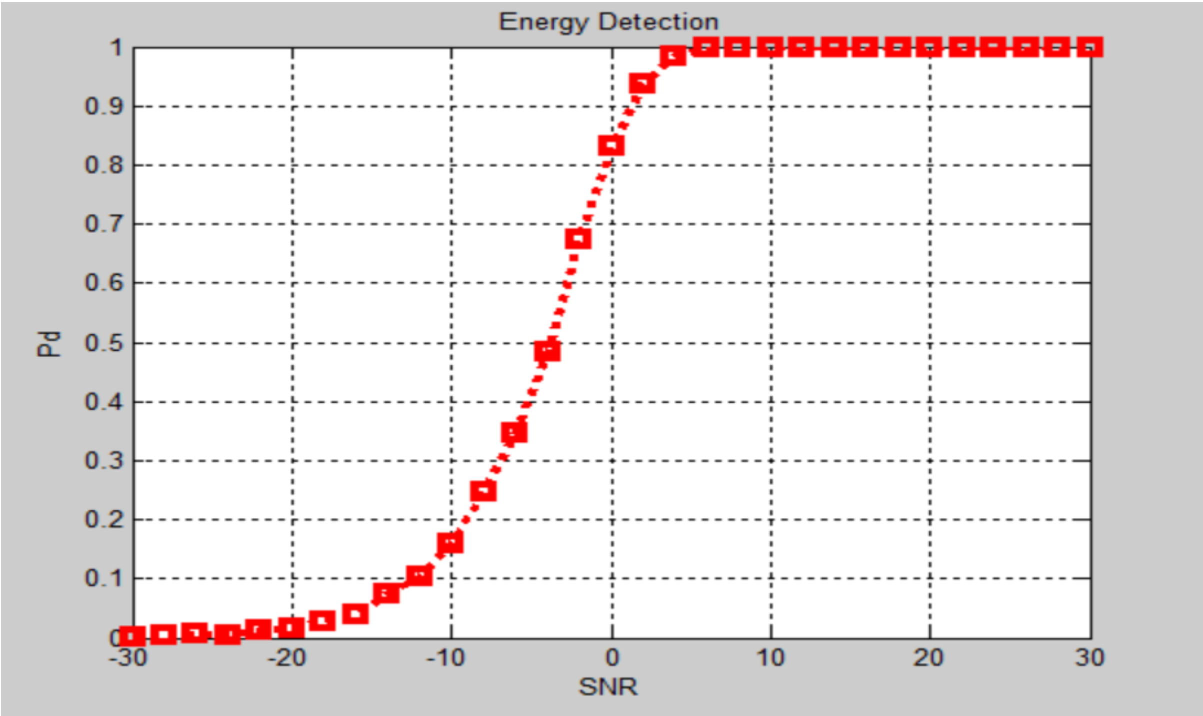

Figure 5-1: Probability of detection vs SNR for ED over Rayleigh Fading Channel

The performance of energy detection algorithm over Rayleigh fading channel is also evaluated in terms of Receiver Operating Characteristics (ROC) curve.

In this case, the number of Monte Carlo iterations is set to 1000 while the number of sensing samples is set to 100. For this particular simulation scenario, a SNR value of 0dB is used. Simulated and theoretical results are depicted in Figure 5-2. It is observed that the probability of detection improves with an increase in the probability of false alarm. It is however, imperative that a balance be maintained between increasing probability of detection at the expense of increasing false alarm, as a high false alarm implies too many missed vacant spectrum opportunities.

Results in Figure 5-2 are also consistent with simulation results in Figure 5-1, which show probability of detection to be approximately 0.8 at SNR value of 0dB when a probability of false alarm is fixed at 0.1.

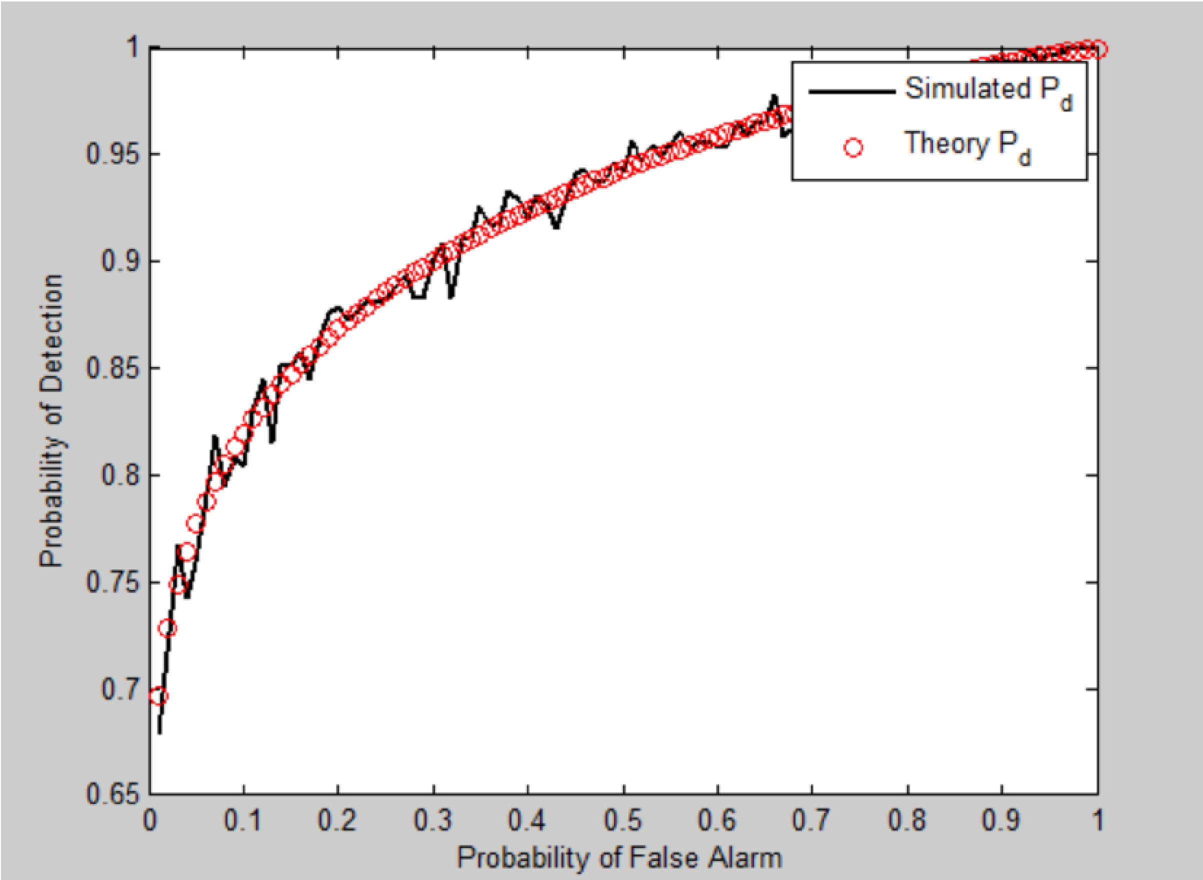

Figure 5-2: ROC curve for Energy Detection under Rayleigh fading channel

5.1.2 Cyclostationary Feature Detection Results

Next, we simulate the performance of the cyclostationary feature detection under the same fading conditions. Simulation results depicting the probability of detection vs SNR are shown in Figure 5-3. It is evident detection performance of CFD is much superior to ED and is high even in a fading channel environment with very low SNR conditions. For instance, with a SNR ratio as low as -25dB, this detector is able to achieve probability of detection above 90%, with the probability of false alarm set to 0.1. At -10dB, the detection performance is more than 5 times better compared to energy detection. The excellent performance of CFD results from its noise immunity. As highlighted in the literature review, CFD exploits cyclostationary features inherent in wireless signals, but are absent in random noise signals thus giving it excellent noise immunity.

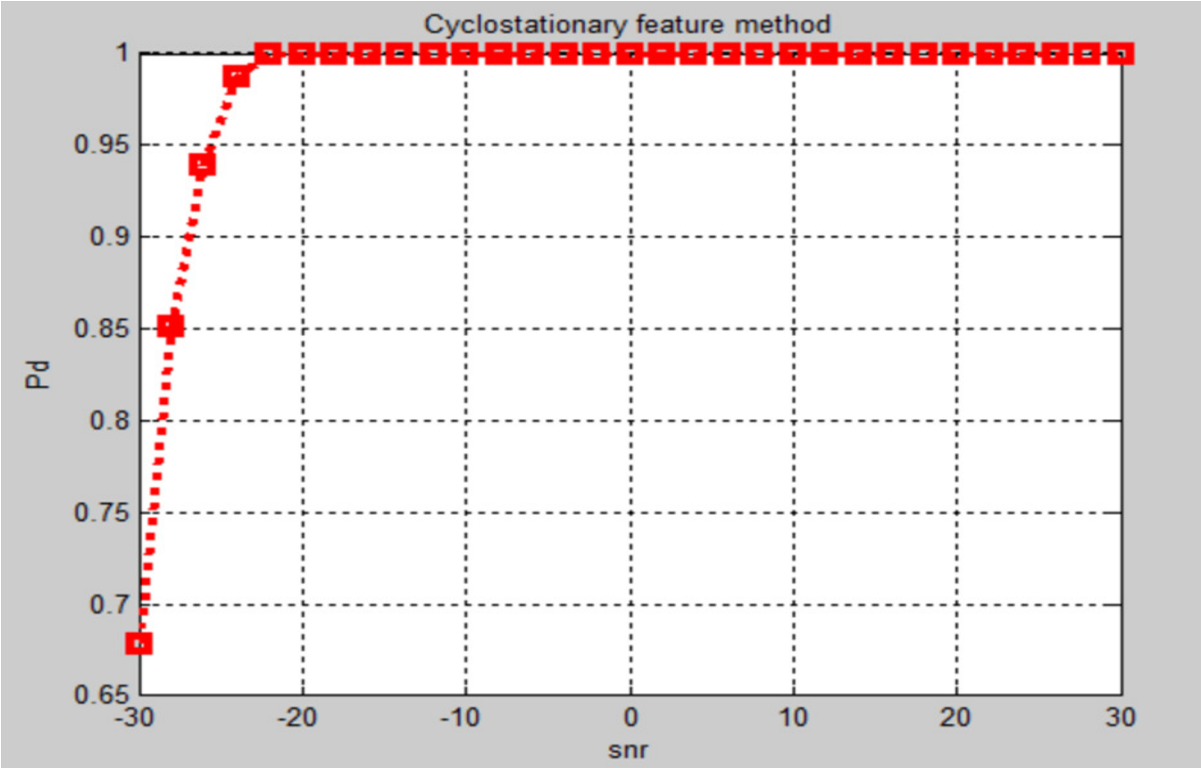

Figure 5-3: Probability of detection vs SNR for CFD over Rayleigh Fading Channel

5.1.3 Matched Filter Detection Results

In this section, we explore performance of the Matched Filter Detector (MFD) method and simulation results for probability of detection versus signal to noise ratio are shown in Figure 5-4. Simulation results show that MFD outperforms the energy detection technique. For SNR of -10dB, the MFD achieves probability of detection of 30%, which is two times better compared to the performance of energy detector at the same SNR value. Comparison of simulation results for MFD and CFD show that the latter is far much superior due to its noise immunity characteristics. In this case, at -10dB CFD achieves a detection performance of close to 100% compared to 30% for MFD.

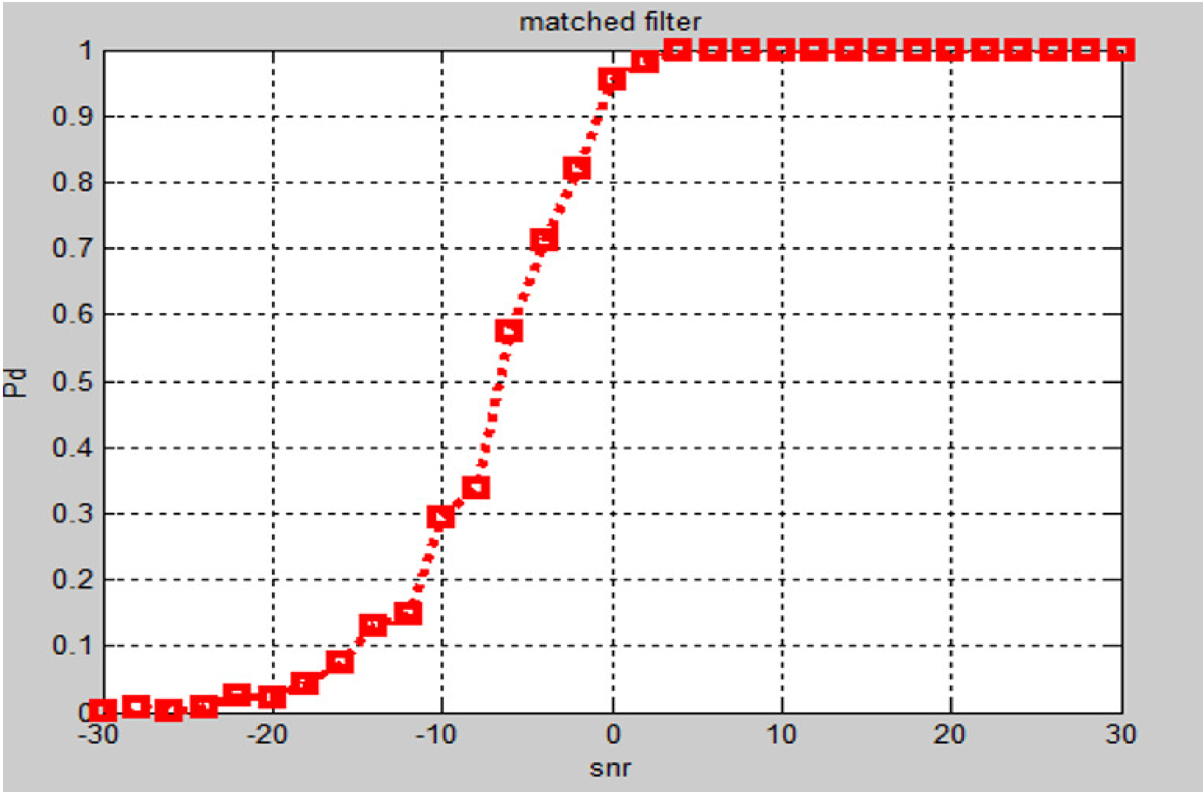

Figure 5-4: Probability of detection vs SNR for CFD over Rayleigh Fading Channel

5.1.4 Co-operative Spectrum Sensing Results

Finally, this section simulates the performance of energy detection based co-operative spectrum sensing under Rayleigh fading channel conditions. In Figure 5-5, using a total of 7 detectors with MAJORITY fusion rule, the performance of co-operative spectrum sensing technique is simulated with results presented in terms of the probability of detection vs SNR. Due to the spatial diversity of the energy detectors, co-operative spectrum sensing technique achieves the best spectrum sensing results compared to the rest of the other methods.

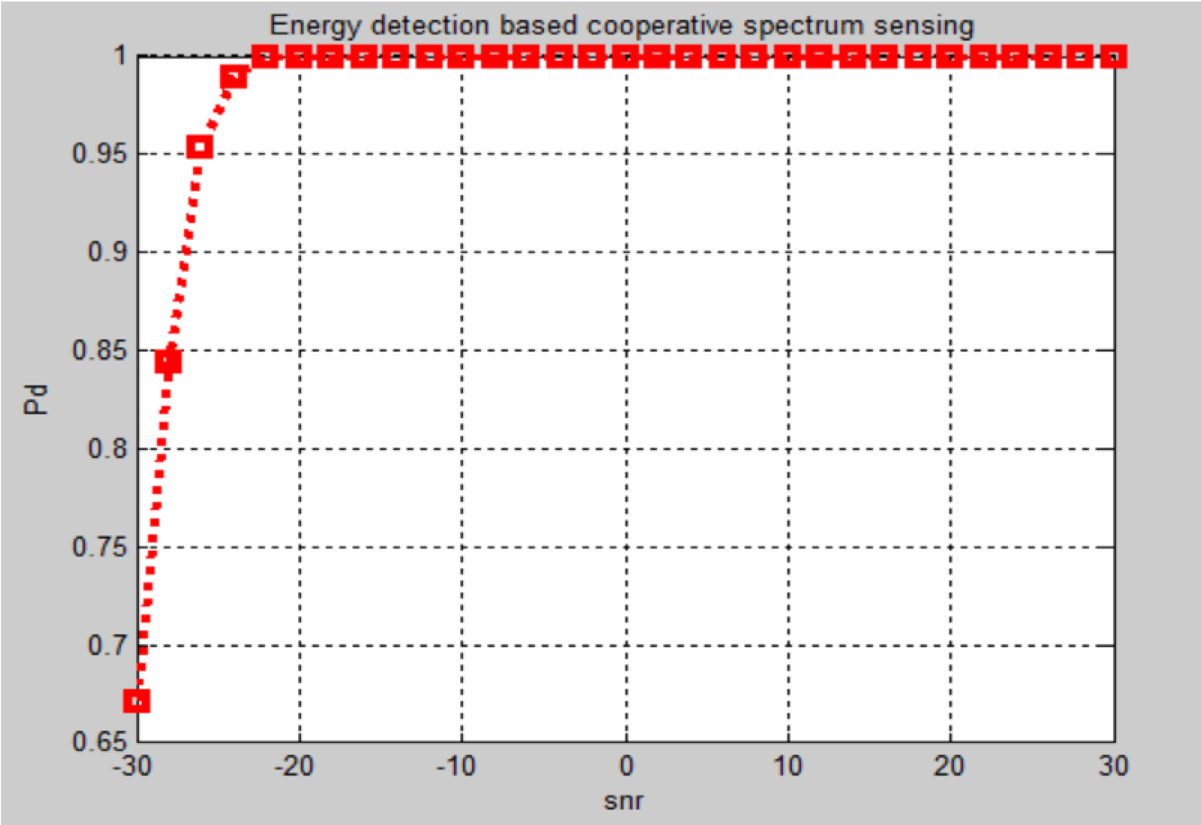

Figure 5-5: Probability of detection vs SNR for Cooperative Spectrum Sensing over Rayleigh Fading Channel

A complementary ROC curve in Figure 5-6 provides further insight into the performance of the co-operative spectrum sensing technique, depicting results in three categories namely theoretical, approximation and simulation. For PFA of 0.1 and SNR of 0dB, the probability of detection achieved by this technique is approximately 90%. This is slightly less than the detection performance achieved by CFD.

Although, the detection performance for co-operative spectrum sensing is slightly less compared to CFD, it is considered more robust due to its spatial diversity advantage and ability to overcome the hidden node scenario.

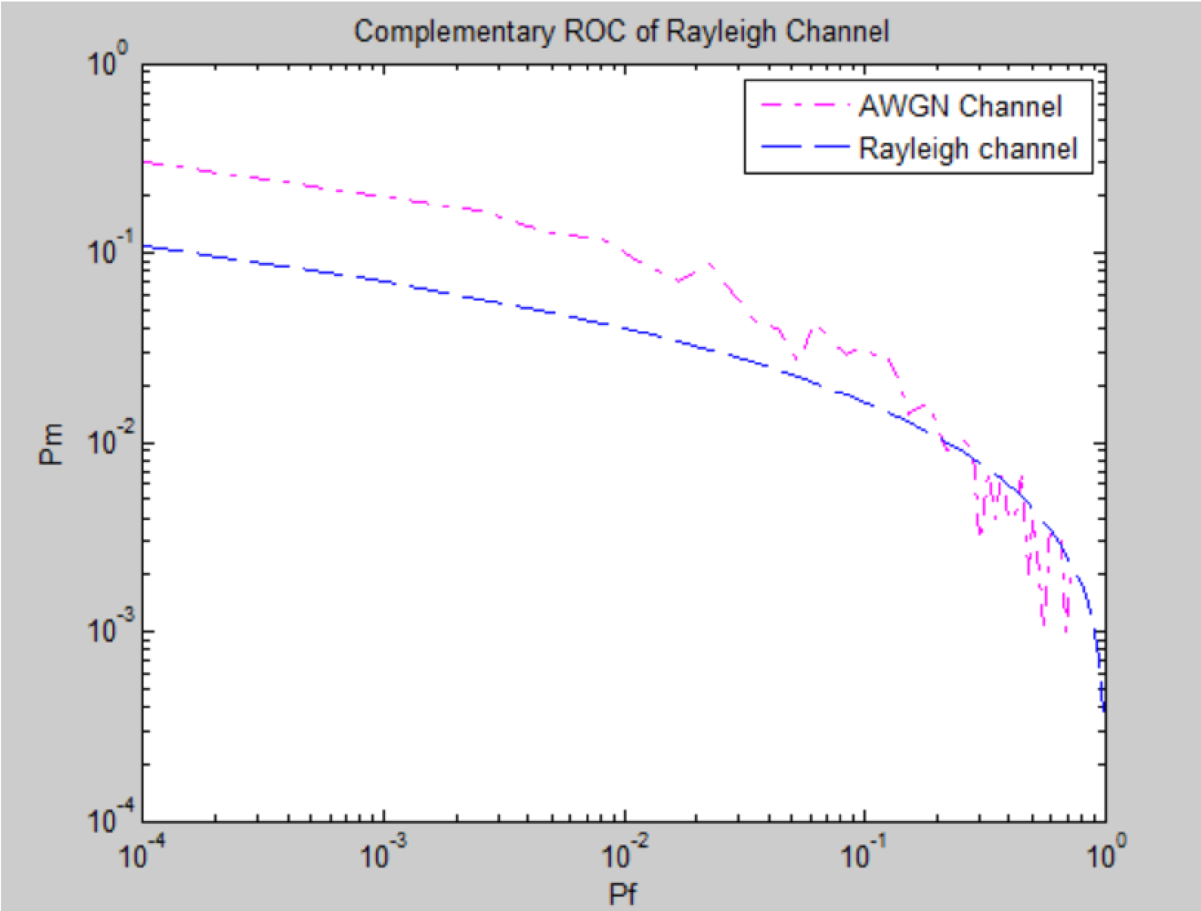

Figure 5-6: Complementary ROC Curve for Cooperative Spectrum Sensing over Rayleigh Fading Channel

5.2 Chapter Summary

This chapter explored the performance of energy detection, cyclostationary feature detection, matched filter detection and cooperative spectrum sensing. Performance evaluation was based on MATLAB simulation results and showed plots for the probability of detection vs SNR, ROC curves as well as complementary ROC curves. Performance of the sensing techniques was analysed under various environmental parameters and comparisons drawn.

Of the four spectrum sensing techniques, CFD offers the best performance under Rayleigh fading conditions. Cooperative spectrum sensing using the OR fusion rule provides the second best performance followed by MFD. Simulation results for ED showed the lowest primary user detection performance.

CHAPTER SIX

6 Conclusions and Recommendations

This chapter summarises the effort of this dissertation by discussing key conclusions drawn out of the simulation results. Furthermore, recommendations on how researchers can build on from this work to improve the usefulness and validity of the results in the future are made.

6.1 Conclusions

As the demand for the spectrum resource continues to soar, as a direct result of the digital transformation, growth in IoT and wireless applications, industry and academia need to proffer solutions for the sustenance of this demand. Cognitive radio has long been widely touted as the most promising solution to the problem of spectrum scarcity, but a lot of work still needs to be done before cognitive radio can be declared a success. Currently, one aspect of cognitive radio where researchers are actively involved with is spectrum sensing. This is perhaps the most critical function where the success of cognitive radio hinges upon. Spectrum sensing ensures that dynamic and opportunistic access to both licensed and unlicensed spectrum is orderly, and interference between wireless applications is minimal.

Firstly, this dissertation presented a background review to the problem of spectrum scarcity. It sought to justify why the study of cognitive radio has gained so much traction in recent times. Through this background review, the dissertation demonstrated how numerous studies have shown that generally, spectrum utilization on licensed spectrum bands is very low, thus presenting bright prospects for cognitive radio as a solution to spectrum scarcity. From this review, a research gap on the study of spectrum sensing techniques under Rayleigh fading channel was identified, leading to the formulation of the main project objective and sub-objectives. A detailed literature review of cognitive radio and enabling technologies, as well as cognitive radio spectrum sensing techniques followed. A firm and comprehensive literature study of spectrum sensing techniques provided a solid foundation for the methodology, design and implementation phases of the project.

This dissertation provides useful insight into cognitive radio spectrum sensing techniques through a Rayleigh fading channel. The major aim was to gain a better understanding of the performance of conventional spectrum sensing techniques, by simulation through a test-bed embedded with fading characteristics. MATLAB software environment was used in performing the simulations. The project considered three transmitter based spectrum sensing techniques, that is Energy Detection, Cyclostationary Feature Detection and Matched Filter detection. In addition, the project investigated the performance of energy detection based spectrum sensing with 7 receivers using OR fusion rule. Employing Receiver Operating Characteristics Curves, complementary ROC curves and plots for Probability of Detection vs Signal to Noise Ratio, an evaluation of receiver performance for the transmitter based sensing techniques and energy based co-operative spectrum sensing was made.

Simulation results show that among the transmitter based spectrum sensing techniques, CFD has superior sensing performance and showed very high probability of detection even at very low SNR values. MFD had the second best performance although performance at low SNR was relatively poor compared to CFD. Energy Detection has the lowest performance in terms of probability of detection, which only improves at higher SNR values. This can be attributed to the fact that ED heavily relies on the gap between the decision threshold and the noise floor, which is a random variable in a fading environment.

Apart from the transmitter based spectrum sensing techniques performance analysis, this project also examined the effects of co-operating energy detection equipped receivers on spectrum sensing performance through a Rayleigh fading channel. ROC curves and a plot of probability of detection versus signal to noise ratio analysis signify an increase in detection performance. This demonstrate that co-operation of receivers enhances performance, and more importantly, is useful in mitigating signal uncertainties in a fading channel environment. Simulation results also demonstrate how the spatial diversity of co-operating nodes can overcome poor detection performance that may result from the hidden node scenario.

6.2 Recommendations

From the foregoing, it is quite apparent that simulations of spectrum sensing techniques using a MATLAB SDR signal provided valuable insight into the performance of spectrum sensing techniques through a Rayleigh channel. However, practical implementation of the project, using a combination of hardware signal receivers and software manipulation of the signals would be even more interesting from a cognitive radio design point of view. This is useful in ascertaining and validating the adopted approach in this project in a real world scenario.

In this regard, Software Defined Radio transceivers such as the USRP, shown in Figure 6-1 below, can be used to generate or capture real world signals. The signals can be manipulated in software through applications such as GNU radio to obtain digital samples that can then be analysed in MATLAB to determine and evaluate performance of spectrum sensing techniques.

Figure 6-1: USRP Transceiver Hardware for Software Defined Radio

Experiments using this approach would add two practical dimensions to the analysis of the performance of spectrum sensing, in the sense that the signal being analysed is now a real signal through a real world environment. Added to this, the channel parameters such as channel gain and delay embedded in signal propagation are derived from the environment instead of the arbitrary values used in the simulations of this work.

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